INTERNATIONAL MONETARY FUND

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

Soumya Bhadury, Bhanu Pratap, and Jay Surti

WP/25/216

2025
OCT

WORKING PAPER

 WP/25/216

IMF Working Paper
Monetary and Capital Markets Department

Emerging Market Cycles: Twin-Balance Sheet Conditions and Macro-Financial Linkages
Prepared by Soumya Bhadury*, Bhanu Pratap†, and Jay Surti‡

Authorized for distribution by Marina Moretti
October 2025

ABSTRACT: This paper empirically examines the dynamic linkages between financial conditions and economic growth across 18 major emerging market economies over the last two decades and the role that fiscal and trade balances play in shaping such associations. Using a reduced-form multivariate autoregressive state-space model, we document two opposing forces – growth-enhancing and growth-inhibiting linkages – that characterize macro-financial dynamics in these countries. Easing of domestic financial conditions is associated with stronger near-term GDP growth, a growth-enhancing link, albeit this acceleration in growth is followed by a tightening of financial conditions that can adversely impact future growth outcomes, a growth-inhibiting link. Both linkages are statistically significant at high frequencies for nearly half of the countries in our sample and appear to be driven by a weak twin-balance sheets condition of high public debt and external imbalances. External factors, notably the global financial cycle, are shown to play a crucial role in amplifying this feedback loop between economic growth and financial conditions.

JEL Classification Numbers:	C53, E32, E44
Keywords:	Macro-financial linkages; emerging markets; twin-deficits; financial conditions; MARSS model; Kalman filter

Author's E-Mail Address:	soumyasbhadury@rbi.org.in bhanupratap@rbi.org.in JSurti@imf.org

∗ Reserve Bank of India.
†Reserve Bank of India.
‡International Monetary Fund.

WORKING PAPERS

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

Prepared by Soumya Bhadury, Bhanu Pratap, and Jay S. Surti[1]

[1] The authors gratefully acknowledge feedback and comments from Viral Acharya, Rodrigo Alfaro, Thorsten Beck, Makram El-Shogi, and seminar participants at the 7th HenU-INFER Workshop on Applied Macroeconomics held at Henan University, Henan, China. The authors also gratefully acknowledge assistance from Sruti Tiwari. The views expressed in this paper are the authors and should not be attributed to their organizations.

Contents

Introduction

This paper brings together two hitherto separate strands of research on macroeconomic cycles, i.e., the interaction of business cycles with financial conditions and the macroeconomic consequences of crowding out, to shed fresh light on the nature of shock transmission in emerging market economies. Our study covers 18 emerging market economies that collectively account for over a third of global GDP in nominal terms, equivalent to 46 percent in purchasing power parity (PPP) terms. Our analysis spans the last two decades, starting in 2000, a period marked by significant intertemporal variation in macro-financial conditions, including severe financial turmoil, economic crises, credit booms and busts, and growth spurts and slowdowns, both globally and in these countries.

Theory provides compelling narratives of the dynamic interaction between financial conditions and business cycles.[2] Economic expansions are accompanied by easy financial conditions and buoyant asset valuations which, over time, breed balance-sheet vulnerabilities in the household, corporate, financial, and public sectors, in the form of excessive leverage and asset-liability mismatches. Once sufficiently high, these imbalances amplify the macro-financial impact of shocks, inducing rapid tightening of financial conditions and abrupt deleveraging that slows growth and may trigger recessions.

Empirical evidence supports the view that easing of domestic financing conditions boosts growth and that credit aggregates and balance-sheet leverage have predictive value for future risks to growth, including for recessions, in advanced economies.[3] The build-up of balance-sheet vulnerabilities in key sectors of the economy takes several quarters, while a boost to growth generated by an easing of financial conditions tends to contribute to the maintenance of accommodative conditions in the interim, as evidenced for example, by Adrian et al.'s (2022) estimated term structure of growth-at-risk.[4] This could reflect capital markets pricing in a stronger corporate outlook, boost to households' income and wealth, and the lowering of sovereign risk associated with a more robust growth environment.

For our sample emerging market economies, several model specifications—bivariate Granger causality tests, vector autoregression with exogenous variables (VAR-X), multi-country panel vector autoregression (VAR)—commonly find a near-term growth boosting effect of an (exogenous) easing of financial conditions.[5] [6]

When using a state space system to model the dynamic interaction of growth and financial conditions, an additional and novel regularity appears. Our results indicate that the relationship between domestic financial conditions and the real economy in these countries is driven by the interaction of two opposing forces which we call a *growth-enhancing* effect and a *growth-inhibiting* effect. As noted above, in most of

[2] Theoretical studies that analyze this interplay between macroeconomic cycles and financial stability include Mendoza (2002, 2010), Jeanne and Korinek (2010), Bianchi (2011), Gorton and Ordoñez (2014), Brunnermeier and Sannikov (2014), and Bianchi and Mendoza (2018), among others. See Adrian and Liang (2018) for a recent survey.

[3] For example, Schularick and Taylor (2012), Jord`a et al. (2013), Surti et al. (2017), Adrian et al. (2019, 2022), Greenwood et al. (2022), and Krishnamurthy and Muir (2025).

[4] Our model coefficients capture one-quarter-ahead dynamics (short run), not medium-term tail-risk effects. The quantile regression and twin-balance-sheets deficits results point to state dependence and amplification consistent with vulnerability buildup. Thus, the two approaches are complementary.

[5] Our approach to building indexes of financial conditions is based on integrating information across a range of price-of-risk variables (spreads and changes in asset valuations and volatility) as in Adrian et al. (2019); global trade and financial indicators; and aggregates (leverage and credit cycle variables). See also Surti et al. (2017), Barajas et al. (2021) and Arrigoni et al. (2022) for recent work on constructing such indexes, including references to the very rich literature on this topic.

[6] Mian et al. (2017, 2020), Adrian et al. (2022), Greenwood et al. (2022), and Acharya et al. (2024) cover a select, small number of emerging market economies, typically in unbalanced panels where, in some cases, major episodes of economic recessionsthat were accompanied, or preceded by financial and banking crises are omitted due to data unavailability.

the emerging market economies that we study, an easing of financial conditions stimulates economic growth in the near-term, a growth-enhancing effect. In addition, our analysis uncovers a growth-inhibiting link that operates at short horizons and could make positive-growth impulses self-limiting. Specifically, a positive growth impulse in one quarter tends to tighten emerging market economies' financial conditions in the following quarter.

Our findings show that the growth-inhibiting effect could unfold fast. Our baseline results indicate that a one standard deviation (sd) easing in emerging markets' financial conditions (EMFCI) is followed by a 0.46*sd* increase in their annual median GDP growth (EM-GDP) the next quarter, equivalent to 82 bps.[7] Conversely, a one-*sd* increase in emerging markets' median GDP growth is followed by a 0.2*sd* tightening in their financial conditions in the next quarter. Hence, while an easing of financial conditions triggers a near-term growth acceleration in emerging market economies, this could be followed by a re-tightening in financial conditions that leashes the pace and duration of the initial growth spurt.

This growth-inhibiting link is amplified when we incorporate global financial conditions into the state-space model. A one *sd* increase in EM-GDP then results in a 0.27*sd* tightening in EMFCI in the next quarter. This highlights the robustness of the bi-directional interaction between domestic economic activity and financing conditions in these countries and is important given the secular increase in the global trade and financial integration of emerging market economies in the last few decades.[8]

What could be driving these dynamics in emerging market economies? The 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.[9] 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 emerging market economies, domestic financial markets may lack adequate depth and could be subject to significantly greater informational and infrastructural frictions. Importantly, in some of them, the growth-elasticity of credit supply to the private sector may be significantly attenuated by *crowding out* due to existing, high levels of fiscal and external imbalances. For such emerging market economies, growth accelerations are more likely to be short-lived because the induced increase in domestic demand quickly tightens domestic and/or external credit and financial conditions due to the prevailing state of stretched balance sheets. In a number of emerging market economies, fiscal deficits are high and some of them also carry large current account deficits. Such imbalances necessitate substantial external financing to maintain domestic consumption.[10] When higher growth stimulates demand for private credit, it must compete with debt refinancing and government borrowing due to elevated debt levels and external imbalances. This can result in a rapid tightening of domestic financial conditions which reduces the aggregate supply and raises

[7] EMFCI is standardized; higher values denote tighter financial conditions. An 'easing' is a decline in EMFCI.

[8] See Obstfeld and Taylor (2004), Bekaert et al. (2011), Surti et al. (2016), Bruno and Shin (2020), and Acharya and Vij (2024). The global financial cycle literature provides insights into the simultaneous movement of gross capital flows, credit growth, leverage, and risky asset prices, e.g., Obstfeld (2015), Rey (2016), and Miranda-Agrippino and Rey (2022).

[9] See, for instance, Claessens and Köse (2013) and Sufi and Taylor (2022).

[10] These twin deficits—fiscal and current account—render countries vulnerable to financial crises, including sudden stops that are marked by large and sudden current-account reversals and can result in large decreases in asset prices, sharp depreciation in real exchange rates, and even deep recessions. Several studies have explored the theoretical and empirical aspects of such episodes from an open-economy perspective, e.g., Joyce and Nabar (2009), Korinek and Mendoza (2014), Eichengreen and Gupta (2016), Akinci and Chahrour (2018), Bianchi and Mandoza (2020), and Davis et al. (2023).

the cost of funds required for further growth.[11] Decomposing the components of domestic demand and rerunning the state-space model, we find that the growth-enhancing effect operates primarily through the positive impulse the easing of financial conditions exerts on private consumption and investment. A high stock of public debt tends to crowd out scope for expansion in private spending, thereby limiting and shortening the beneficial growth impact of easier financial conditions.

We apply a two-way sample split to check whether the subsample of emerging market economies that have large fiscal and current account deficits also exhibit a more consistent pattern of interacting, significant growth-enhancing and growth-inhibiting linkages. Our results indicate that emerging market economies facing twin-deficits conditions are much more likely to be subject to both linkages. Moreover, the prevalence of twin-deficits conditions also tends to significantly amplify the macro-financial implications of an exogenous tightening of domestic financial conditions, lending support to both, the *sudden-stops* and *crowding-out* hypotheses. How significant is this amplification? A quantitative comparison of impulse responses shows that the strength and persistence of the reduction in growth following an exogenous tightening of domestic financial conditions is significantly higher in emerging market economies with weak twin-balance sheets conditions. For such countries, economic growth is significantly reduced for four quarters while the impact is quantitatively smaller and lasts for at most one quarter in other Emerging market economies.

Our paper makes two key contributions to the extant literature on macro-financial dynamics. First, our findings on the prevalence of both growth-enhancing and growth-inhibiting linkages offer a fresh perspective on the association between economic and financial cycles across countries. The relatively rapid emergence of financial tightness, particularly in economies with weak twin balance-sheets conditions, highlights the distinct mechanisms that influence macro-financial dynamics. While weak twin balance-sheets conditions can undermine the sustainability of growth accelerations in these economies, external factors—particularly the global financial cycle also significantly affect the ability of twin-deficit economies to sustain growth spurts.

Second, from a modelling perspective, we propose a reduced-form, multivariate state-space model to analyze the two-way association between real and financial cycles and incorporate the impact of the global financial cycle. Our empirical model is inspired by the *predator-prey* class of models commonly used in ecological studies of population dynamics.[12] This approach is suited to our objective of capturing endogenous macro-financial cycles with a minimal set of assumptions that avoid unnecessary complexity. More intricate frameworks, such as agent-based models, rely on several behavioral assumptions that could obscure underlying causes of cycle emergence (Gross, 2022). Our approach focuses on delineating the bi-directional relationship between growth and financial conditions and identifying factors that may amplify or dampen this interaction.[13] To our knowledge, our paper is the first one to model the dynamic interaction of

[11] The crowding-out nature of government borrowing programs has also been extensively documented in the literature, e.g., Blanchard and Perotti (2002), Blanchard (2003), Furceri and Sousa (2011), Afonso and Sousa (2012), and Agnello et al. (2013). The adverse impact of crowding out is exacerbated in less developed financial systems due to limited funding sources and greater reliance on the banking sector; see, for e.g., Park and Meng (2014), Funashima and Ohtsuka (2019), and Liaqat (2019).

[12] See Paine (1980), Frost et al. (1995), Ives (1995), Tilman (1996), Ives et al. (1999, 2003), and Hampton et al. (2013).

[13] See also Blanchard (2018) and Claessens and Kose (2018). Predator-prey models, particularly those with System Dynamics Model (SDM) structures, a class of nonlinear aggregative disequilibrium models, is linked to the work of Kalecki, Harrod, Goodwin, and Minsky since the early 1970s. Early contributions include Torre (1977), Taylor and O'Connell (1985), Foley (1987), Semmler (1987) and Jarsulic (1989), who developed nonlinear aggregate models often incorporating multiple differential equations. Many of these studies, particularly those drawing on Minsky, emphasize the critical role of credit. A survey of models that incorporate Minskyian elements is provided by Nikolaidi and Stockhammer (2018), and Gross (2022). Models exploring procyclical leverage, e.g., Brunnermeier and Sannikiv (2014) and Danielsson et al. (2016), are also grounded

(continued…)

growth and financial conditions in a state-space framework and to apply it to study its drivers. Its utility, in our view, is reflected in its ability to capture the prominence of a statistically and quantitatively significant growth inhibiting link that appears to be associated with the existence of twin-deficits conditions. For our sample of emerging market economies, alternative statistical models, such as panel VARs, are unable to capture this link. In fact, the multivariate state-space framework is particularly well suited to emerging market economy settings, where quarterly aggregates are subject to frequent revisions and measurement noise, and models estimated directly on observables can attenuate feedback. In such a setup, the Kalman filter/smoother extracts the signal from noisy observables on financial conditions and growth outcomes, yielding cleaner dynamics. The framework remains reduced-form—recovering predictive, bidirectional associations rather than causal multipliers—while mitigating measurement-error bias that can obscure the response of growth outcomes on financial conditions. It also accommodates an exogenous global financial cycle variable while allowing for the modeling of the dynamic interaction of growth and financial conditions. Together, these features deliver sharper near-term predictive content from financial conditions to growth and reveal complementary feedback that is otherwise hard to detect.

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 the details of the multivariate autoregressive state-space (MARSS) model employed in this 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 at both the aggregate emerging markets level as well as at the country level. Section 5 concludes. Some technical details are provided in the appendix.

in SDMs. In the macro-financial domain, our model applies a predator-prey structure to capture the feedback loops between macroeconomic and financial conditions.

Methodology

We start this section by providing a concise conceptual overview of our analytical framework. We then present the principal empirical framework motivated by the plausibility of, and designed to capture, bidirectional, dynamic interaction due to feedback between financial conditions and output growth.

Conceptual Framework

We aim to capture the dynamic associations between financial conditions and growth as well as understand how balance-sheet vulnerabilities in certain economic sectors of emerging market economies can impact the nature and persistence of macro-financial transmission of exogenous shocks in these countries.

Consider a positive exogenous shock which eases domestic financial conditions worldwide. This would lead to increased lending and risk-taking that boosts domestic economic activity and growth in the near-term in emerging market economies. This is an illustration of the growth-enhancing effect or phase of macro-financial cyclical interaction.

Rapid and sustained credit expansion during such periods of loose financial conditions would lead to the buildup of balance-sheet vulnerabilities in the economy that can serve to eventually amplify the growth and financial stability impact of adverse exogenous shocks, such as the Covid-19 pandemic. 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. Figure 1 presents a summary of our framework that captures the macro-financial associations.

The length of time over which the phase of elevated growth and loose financial conditions prevails in emerging market economies may depend on two factors. First, domestic financial markets and savings intermediation capacity are shallower in these countries compared to advanced economies. This may constrain the elasticity of credit supply and the market liquidity available to meet higher credit demand that typically arises in response to the positive growth impulse provided by the easing of financial conditions. Second, key sectors of the economy often face significant balance-sheet vulnerabilities. For example, high sovereign indebtedness and large current account deficits require financing through substantial fiscal and macroeconomic borrowing both domestically and abroad. These vulnerabilities may absorb much of the limited 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 emerging market economies 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 reached 5.1 percent, compared to 3.4 percent during a tranquil three-year period. 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. When balance-sheet vulnerabilities grow beyond a critical level during a credit boom, the macro-financial impact of adverse exogenous shocks can be amplified.

Several factors and linkages are potentially important across both advanced and emerging market economies in propelling the growth of balance sheet and financial market vulnerabilities.

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 typically exerts a pronounced wealth effect that makes households and firms more inclined to spend, invest and hire. However, when asset prices become inflated and disconnected from underlying fundamentals, risks and financial imbalances arise. If a negative shock hits the economy, it can rapidly lead to tighter financial conditions. Both advanced and emerging market economies have seen surges in asset prices followed by long periods of financial instability.[14]

A second mechanism is the procyclicality of bank lending and risk-taking. During the pre-GFC boom (2003–07), abundant liquidity and compressed spreads coincided with loose underwriting and rapid balance-sheet expansion that ultimately amplified the severity of the bust, consistent with the disaster myopia and neglected-risk channels (IMF, 2009; Gennaioli, Shleifer, and Vishny, 2012). Nonetheless, in the post-crisis period, persistently low rates and volatility again encouraged a search for yield, with risk premiums and covenants moving procyclically (BIS, 2014). The institutional-memory hypothesis—that managers gradually forget the last bust and ease standards as expansions mature—provides a micro-foundation for these patterns (Berger and Udell, 2004). Separately, Acharya and Steffen (2015) have argued that herd behavior was visible in the lead up to, and during the euro-area sovereign debt crisis (2010–13), when banks crowded into high-yield domestic sovereigns funded at short maturities, reinforcing the sovereign–bank loop. These episodes are consistent with the behavioral and institutional mechanisms underpinning the macro-financial feedback we estimate.

A third aspect is external factors that may also have an impact on the interaction between growth and financial conditions in emerging market economies. Capital flows into these countries tend to ease credit constraints for corporations and households directly (when corporations raise funds in global capital markets) and because 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 the domestic economy. In the event of an abrupt, substantial decline in international net capital flows—so-called sudden stops—domestic financial conditions can undergo rapid tightening, and growth can slow and even give way to an economic contraction (Joyce and Nabar, 2009; Korinek and Mendoza, 2014; Akıncı and Chahrour, 2018; Davis et al. 2023). Such episodes are usually accompanied by a significant increase in credit risk spreads (interest rate differentials), negative asset returns, and high volatility, sometimes resulting in recessions. The impact of such crises episodes is amplified in countries with high current account deficits (Eichengreen and Gupta, 2016).

Finally, domestic fiscal imbalances also tend to influence macro-financial associations 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* the private sector by causing an increase in interest rates leading to lower investments (Blanchard and Perotti, 2002; Blanchard, 2003). Most empirical evidence now favors the *crowding-out* effect of government spending programs (Furceri and Sousa, 2011; Afonso and Sousa, 2012; Funashima and Ohtsuka, 2019; Liaqat, 2019; Park and Meng, 2024).

[14] Evanoff et al. (2012) and Scherbina (2013) review the literature on asset price bubbles.

In our empirical implementation, these mechanisms map to a range of model inputs: (i) asset-price inflation and price-based stress enter via a *Domestic Price of Risk* block (equity returns/volatility, term/corporate/interbank spreads, exchange market pressure index); (ii) balance-sheet vulnerability is captured through indicators such as credit to the private sector, market based measures of bank solvency risk, fiscal deficits and leverage;[15] and (iii) correlated risk-taking/herding, proxied by a global financial conditions indicator. We do not claim structural identification of herding; rather, the evidence of a significant GDP→FCI association is consistent with common risk-taking.

Econometric Model

Analyzing macro-financial dynamics in emerging market economies requires a framework that (i) accommodates bi-directional interlinkages between financial conditions and growth; (ii) separates information signals from noisy quarterly aggregates; and (iii) allows global factors to influence domestic macro-financial interactions. Hence, we use a MARSS model to recover predictive, reduced form interlinkages between latent financial conditions and GDP growth, both at the aggregate emerging markets sample level and at the country level. Two practical considerations motivate this choice. First, models estimated directly on observables can suffer attenuation bias when measurement error is non-trivial. The state-space approach explicitly estimates the measurement noise and filters it out. Second, it flexibly incorporates an exogenous global financial cycle indicator while allowing domestic feedback to operate.

Our specification is inspired by models of population dynamics, namely the *predator-prey* class of models, rooted in ecological studies.[16] Thus, our baseline empirical model is specified by (1) and (2) given below along with key model assumptions:

A1 (State dynamics). Latent states $x_t = (\mathrm{Ft}, \mathrm{Gt})'$ follow a stable MARSS (1) process.

A2 (Measurement). Observables are noisy measures of states.

A3 (Loading matrix). $Z = I_2\,; n = m = 2$; where n is the number of observable variables, i.e., EMFCI, defined as the median of the country-level FCIs in any given quarter, and EM-GDP, the median of the country level (annualized) GDP growth rate in the same quarter; m is the number of latent states. Both observable variables are treated as noisy one-for-one readings of their corresponding latent states.

A4 (Interpretation). The matrix B captures reduced-form state dynamics.

$$y_t = Zx_t + a + v_t;\ v_t \in MVN\ (0, R) \qquad (1)$$

$$x_t = Bx_{t-1} + u + w_t;\ w_t \in MVN(0, Q) \qquad (2)$$

Under the state-space representation, (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, the observed time-series data on financial conditions and output growth are represented by y_t in our case. (2) represents the process equation, with x_t containing state variables. Typically, we have one time series per state-variable and that translates to $m = n$. The x_t equation is termed the state process, with w_t denoting the process error and Q the covariance structure of process error. The model has a stochastic equilibrium, which fluctuates around a mean given by $(I - B)^{-1}u$. (2) in our specification is similar to what Ives et al. (2003) have written as their process equation. The state-space representation is scale-invariant, where u is

[15] The market-based measure of bank solvency risk used in our paper is S-RISK. A description in provided in the next section.

[16] See Paine (1980), Frost et al. (1995), Ives (1995), Tilman (1996), Ives et al. (1999), and Hampton et al. (2013).

the scaling term. A matrix form representation of the process model for the finance-growth dynamics is provided in (3)—(4) below:

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

$$\begin{pmatrix} w_f \\ w_g \end{pmatrix}_t \epsilon\, MVN\left(0, \begin{pmatrix} q_f & 0 \\ 0 & q_g \end{pmatrix}\right) \tag{4}$$

B is the interaction matrix to be estimated in the process model. 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-associations are represented by the off-diagonal terms of the *B* matrix. Thus, b_{ff} is the link of financial conditions on itself (density-dependence); b_{fg} is the link of financial conditions on growth; b_{gf} is the link of growth on financial conditions; and finally, b_{gg} is the link of output growth on itself.

The global financial cycle can significantly influence capital flows, credit expansion, leverage, and asset prices in emerging market economies.[17] Therefore, as a final step, we augment our MARSS model by adding a covariate in the process equation of the model. The state-space model with covariates can be represented as follows:

$$y_t = Zx_t + a + v_t;\ v_t\, \epsilon\, MVN(0, R) \tag{5}$$

$$x_t = Bx_{t-1} + Cc_t + w_t;\ w_t\, \epsilon\, MVN(0, Q) \tag{6}$$

$$\begin{pmatrix} x_f \\ x_g \end{pmatrix}_t = \begin{pmatrix} b_{ff} & b_{gf} \\ b_{fg} & b_{gg} \end{pmatrix} \begin{pmatrix} x_f \\ x_g \end{pmatrix}_{t-1} + \begin{pmatrix} c_{ff} \\ c_{fg} \end{pmatrix} (GFC)_t + \begin{pmatrix} w_f \\ w_g \end{pmatrix}_t \tag{7}$$

C_{ff} and C_{fg} terms capture the contemporaneous linkages of global financial conditions with domestic financial conditions and economic growth in emerging market economies in the model. We invert Rey's global financial conditions index, so that higher values denote tighter global conditions. Throughout, C_{ff} measures the estimated one-period ahead statistical link of the (inverted) global financial conditions index on EMFCI and C_{fg} measures the estimated one-period ahead statistical link of the (inverted) global financial conditions on EM-GDP. Accordingly, $C_{ff} > 0$ means tighter global financial conditions are associated with tighter EMFCI, and $C_{fg} < 0$ means that tighter global financial conditions are associated with reduced EM-GDP next quarter.

The above model is estimated using maximum likelihood (ML) techniques.

To deepen our understanding of the macro-financial dynamics in emerging market economies, we also compare the results from the model described above with those from alternate time-series and panel data models. This comparison helps us analyze how the bi-directional interaction between finance and growth reflected in the presence of growth-enhancing and growth-inhibiting effects is uniquely captured by our state-space model.

VARs are typically estimated directly on observables y_t that satisfy a measurement equation $y_t = Zx_t + a + v_t$. When observables are noisy ($v_t \neq 0$, lag coefficients are biased toward zero; in the classic errors-in-variables case with noise in the regressor, $\hat{\beta} = \beta \times \mathrm{Var(x)} / [\mathrm{Var(x)} + \mathrm{Var}(v)]$. Quarterly aggregates for emerging market economies that are noisy owing to revisions and cross-country aggregation can,

[17] Rey (2016) and Miranda-Agrippino and Rey (2022).

therefore, mute the estimated GDP→FCI link (our b_{fg}). By contrast, the state-space model estimates $\mathrm{R} = \mathrm{Var}(v)$ and uses the Kalman filter to extract the latent states x_t, reducing attenuation and yielding cleaner dynamics. Identification choices in Appendix C (e.g., a Cholesky ordering with GDP ordered after FCI) restrict only the impact response, i.e., at multi-quarter horizons the restriction does not bind. The insignificance of b_{fg} in observables-based VAR is consistent with attenuation from measurement error.[18] This attenuation helps explain why the directional association of GDP→FCI embodied in estimates of b_{fg} is weak in VARs yet present in the state-space estimates. Even without structural identification of fiscal or credit multipliers, the estimated latent states provide sharper near-term dynamics for forecasting and early-warning, and they complement Growth-at-Risk applications by supplying a less noisy, jointly estimated macro-financial state for tail-risk analysis. We briefly discuss these results in Section 4 and provide further details in Appendix C.

[18] Small true effects or low power can also contribute.

Data

This section provides an overview of the data, including the country and time sample utilized for our analysis. We also discuss the construction of the FCI for the emerging market economies covered in our study. We begin 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 EM-level. Thereafter, we present and analyze the aggregate emerging market economies' financial conditions index (EMFCI).

Data and Sample

Our sample of emerging market economies includes Argentina, Brazil, Chile, China, Colombia, the Czech Republic, India, Indonesia, Korea, Malaysia, Mexico, Philippines, Poland, Russia, Slovakia, South Africa, Thailand, and Türkiye.[19] We construct a quarterly, cross-country dataset consisting of various macro-financial indicators using data sourced from Bloomberg L.P., NYU V-lab, Bank for International Settlements (BIS), and the International Monetary Fund's International Financial Statistics (IMF-IFS). The MARSS model is estimated using a quarterly dataset spanning 2000:Q1 through 2019:Q4.

Our empirical model uses year-on-year growth rate of real GDP (percent) as a measure of output growth. We construct country-specific FCI to capture domestic financial conditions for our sample emerging market economies. Data on global financial conditions is taken from Miranda-Agrippino and Rey. We invert their index of global financial conditions as noted in Section 2.2 so that higher values indicate tighter global conditions. The concept and construction of country-specific FCI is detailed below.

Financial Conditions Index

Concept

In a shock-free environment, financial vulnerabilities tend to accumulate gradually and may silently spread within the financial system and macroeconomy. Once they breach a critical threshold, such vulnerabilities can significantly amplify the impact of an adverse shock on the economy. Therefore, financial vulnerabilities are crucial for understanding how the health of the financial system as well as the economy may evolve over time. Combining information on stress indicators and vulnerabilities can provide a synthetic, forward-looking measure of financial conditions in an economy that can convey early warnings effectively to markets and policy makers.

Following Krishnamurthy and Muir (2025), 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* blocks. These blocks may directly or indirectly impact

[19] 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. Under the IMF classification, the Czech Republic, Korea and Slovakia are designated as advanced economies. However, major market indices (e.g., FTSE Russell, MSCI and FTSE Equity Country Classification respectively), continued to classify them as emerging market economies for most or all of our sampling horizon. For this reason, as well as sensitivity to common factors such as global financial conditions, we include them in our sample of emerging market economies.

financial conditions in the economy. Figure 2 summarizes our conceptual construction of a FCI impacted by various measures of financial stress and vulnerabilities emanating from different sectors of the economy.

One measure of financial stress is the *domestic price of risk (DPOR)* which includes interest rate spreads relevant for the borrowing costs of the corporate and government sectors as well as returns and volatility across different asset classes. An increase in financial stress is often reflected in rising interest rates (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 the implied options volatility of the exchange value of the domestic currency (against the US dollar) and indicators of exchange rate market pressures are likely to be associated with tighter domestic financial conditions. Finally, macroeconomic indicators that capture economic activity and real estate prices also provide important signals related to the overall stress and tightness in the domestic financial system.

The level and duration of the likely adverse impact from shocks to the economy and the financial system can be inferred from the balance sheet vulnerabilities of key stakeholders, such as financial institutions and the government. Such indicators, encompassing aggregate balance sheet metrics like private sector leverage, the credit-to-GDP gap, fiscal balances, and government debt, tend to exhibit gradual, but potentially more informative signals about the health of the financial system over a longer time horizon.

Input Variables

To capture stock market performance, we use the variable *EqReturn* which represents the returns of large-cap companies in each country. For equity returns volatility, we use the Bloomberg-sourced *EqVol30* variable, which measures the average 30-day volatility of large-cap listed companies. Information regarding tightness in bank financing of economic activity is provided by the corporate sector prime lending rate, *PLR*. *OptionVol3m* is the implied options volatility of the exchange rate of domestic currency with respect to the US$. *Term Spread* measures the difference in yields between long-term government bonds and short-term treasury bills. *Corporate Spread* measures the difference between CEMBI corporate bond yields and short-term treasury bill yields, i.e., the corporate bond market's credit risk premium. *Interbank Spread* is the difference between the 3-month interbank lending rate and the short-term treasury bill, proxying interbank market liquidity and tightness.

Turning to vulnerability indicators, the variable *Credit* provides information on outstanding leverage of the private non-financial sector. Information regarding the systemic (risk) impact of distress in the domestic banking sector in our emerging market economies is represented by *SriskUT,* which measures the market capitalization weighted-average systemic risk for the banking sector as estimated by New York University's V-Lab—it aids in assessing the overall stability and vulnerability of the domestic banking system in the economies in our sample.[20] The exchange market pressure index, *EMPI*, captures total pressure on the exchange rate that has been managed through foreign exchange intervention or through exchange rate movements (Girton and Roper, 1977; Eichengreen et al., 1996; Levy-Yeyati and Sturzenegger, 2005). Key fiscal indicators are included in our analysis—*Debt-to-GDP*, measured by taking gross government debt as a percentage of domestic GDP, provides information on the long-term viability of public finances, whereas *Primary Balance* reflects the government's flow fiscal situation (excluding interest payments).[21] Finally, variables related to the real estate market and economic activity are also included in our study. *Real-estate prices* include both residential and commercial property prices. *Industrial Production* provides an index of

[20] Acharya et al. (2017) and Brownlees and Engle (2017) provide a thorough discussion of this measure.

[21] Primary balance = Total revenues less total expenditures, excluding gross interest payments.

industrial activity in the economy. Details on the number of countries, variables used and data sources for constructing the country-wise financial conditions are summarized in Table 1.

Index Construction

We now turn to the DFM used to combine various stress and vulnerability indicators into a single, composite measure of financial conditions at the country-level. Following 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, i.e., an AR(1) process. Thus, the empirical model can be represented in matrix-form using (8) and (9):

$$Z_t = \Gamma F_t + \xi_t \qquad (8)$$

$$F_t = AF_{t-1} + B\nu_t \qquad (9)$$

where Z_t is a vector of stationary observed variables driven by a vector of unobserved dynamic factors, F_t, in a linear combination determined by a loading vector Γ. Series- specific idiosyncratic components are captured by the vector ξ_t, while ν_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 and its estimation using the Kalman filter approach are discussed in Appendix A.

Subsequently, an aggregate EM-level FCI (EMFCI) is computed from the country-specific FCIs. Figure 3 presents the median, 5th and 95th quantiles derived from the country-specific FCI values, allowing us to assess the dispersion and tail risks associated with domestic financial conditions in our sample of countries.[22] Periods of heightened financial stress when existing systemic vulnerabilities amplified the impact on macro-financial stability, such as the global financial crisis and the Eurozone debt crisis are clearly captured by our financial conditions index for the sample of emerging market economies. As a robustness check, we construct country-level FCI using just the *domestic price of risk* for each country. Our empirical results, discussed in Section 4, remain qualitatively similar when this alternative choice of FCI is used (see also Appendix B).

[22] MARSS model estimates use 2000Q1 to 2019Q4.

Results and Discussion

The presentation of the main findings from our analysis of the dynamic interplay between financial conditions and growth in emerging market economies is divided into three parts. Throughout this section, our focus remains on the interaction matrix *B* and its elements denoted by B_{ij} (recall (3) and (4)).[23]

In the first part, we present results from our MARSS model for emerging market economies in both the benchmark specification, which does not explicitly account for the global financial cycle, and an augmented specification including this exogenous factor. Throughout, we distinguish between country-level FCIs and the EMFCI. Country-level FCIs are constructed separately for each of the 18 emerging market economies in our sample using alternative measures from the suite of indices that progressively integrate financial stress, vulnerability, and (in some cases), real-activity variables. EMFCIs are then obtained by aggregating these country-level measures across the 18 emerging market economies. For our baseline EM-level index (***EMFCI1***), we aggregate the most comprehensive country-level measure by taking the cross-country median each quarter. Since this measure includes real-activity variables at the country-level and may, therefore, mechanically overlap with GDP growth, we also use an alternative EM-level measure (***EMFCI3***), constructed from all-in, country-level indices that exclude real-activity variables. Our EM-level results are robust to using either EMFCI1 or EMFCI3, as well as to alternative choices of country-level FCIs to build the EMFCI. We also analyze the finance–growth relationship across different growth quantiles to assess its strength and direction during tail-risk events. The second part focuses on the country-level analysis, in which we estimate the model separately for each emerging market economy.[24] This exercise allows us to identify whether growth-enhancing or growth-inhibiting linkages dominate in each country, and to assess the statistical significance of these linkages.

The third part examines whether certain macroeconomic characteristics amplify or dampen these linkages. For this sample-split exercise, countries' government debt and current account balances are first scaled by their GDP. We then compute the annual sample (across country) median debt-to-GDP and current account balance-to-GDP for 2000–2019 and average the annual median series to obtain long-term sample average benchmarks. We then compare each country's 2000–2019 average debt-to-GDP and current account balance-to-GDP ratios to these long-term sample benchmarks. This yields a classification of countries into high-debt (HD) or low-debt (LD) and current account surplus (CAS) or current account deficit (CAD) groups depending on whether their domestic long-term ratios exceed or below the benchmark levels. Subgroups such as twin-deficit countries (HD and CAD) can thus be identified, enabling us to test whether a "twin-deficits balance-sheets" condition heightens the sensitivity of growth to financial tightening. We also discuss the role of the global financial cycle in amplifying domestic macro-financial linkages and present simulation results supporting our modelling choices.

Regional Analysis

The estimated coefficients in the interaction matrix of the MARSS model with and without covariates are shown in Table 2(a). As mentioned earlier, we carry out this exercise at the aggregate emerging market economies level by using the median value of the country-level FCIs and median GDP growth for all emerging market economies in our sample represented by EMFCI and EMGDP, respectively. Shown in panel 1 of Table 2(a), our baseline estimates indicate that a one standard deviation (*sd*) easing in EMFCI leads to a 0.46*sd* increase in EM-GDP in the next quarter. This underlines a significant *growth-enhancing*

[23] We read these coefficients as reduced-form linkages, i.e., we do not estimate fiscal or credit multipliers.

[24] Here, we draw on several FCI options that capture different combinations of financial stress and vulnerabilities. Based on out-of-sample forecast comparisons, the all-inclusive FCI measure performs relatively better for most emerging market economies and is therefore used as our baseline country-level FCI in the presentation and discussion of the results.

link at work. On the other hand, a one *sd* increase in EMGDP growth leads to a 0.2*sd* increase in EMFCI the next quarter, which supports the prevalence of a significant *growth-inhibiting* link.

Shown in panel (2), the estimated coefficients are similar when we account for the role of global financial conditions in our model. Model diagnostics reported alongside the estimated coefficients indicate a better fit with data for the model augmented with the global financial cycle indicator. Our results, both with and without the global financial cycle as a covariate, are statistically and economically significant.[25]

These results provide evidence for the presence of both *growth-enhancing* and *growth-inhibiting* effects influencing macro-financial dynamics in major emerging market economies during the last two decades. Consequently, the beneficial impact of exogenous shocks that ease financial conditions in a country on the domestic economy may be short-lived—for a "median" emerging market economy, any resulting growth spurt appears to quickly sputter out as the increase in EM-GDP in turn re-tightens EMFCI in the next quarter.

Our baseline EMFCI measure (EMFCI1) incorporates real activity indicators in addition to stress and vulnerability indicators and there is a possibility that this mechanically amplifies its correlation with GDP growth. To examine whether our results are robust to an EMFCI measure that is independent of contemporaneous real activity, our alternative FCI, EMFCI3 produces results that are qualitatively similar (Table 2(b)). This indicates that our main findings are not driven by inclusion of information related to real sector developments in the FCI.

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* EM GDP growth. We accomplish this by replacing the median GDP growth with a simple average as well as weighted average measures based on weights derived from the World Bank (WB) and the IMF. The results are shown in Table 3(a). Overall, the results are 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 (column 3 of Table 3(a)).[26]

We also assessed whether the *growth-enhancing* and *growth-inhibiting* linkages were more prominent in certain parts of the output growth distribution. We compute different quantiles of GDP growth at the aggregate emerging market sample-level and estimate our model separately for each growth quantile. The results are shown in Table 4(a). 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} attenuating from −0.41 (Q50) to −0.12 (Q95), albeit remaining statistically significant. B_{gf} also gets attenuated and becomes insignificant at the higher quantiles (Q90, Q95). This indicates that the strength of both *growth-enhancing* and *growth-inhibiting* linkages 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. The corresponding robustness check results using EMFCI3, shown in Table 4(b), display similar distributional patterns.[27]

[25] The role of global financial conditions is discussed in greater detail in Section 4.4.

[26] The results for the same exercise using the EMFCI3 measure are reported in Table 3(b).

[27] For robustness, we have estimated quantile regressions at the aggregate EM level using two alternative financial condition measures: ***EMFCI1*** (corresponding to the FCI incorporating information from all stress and vulnerability indicators, including real sector indicators—this is the DPOR-ALL index described in Appendix B) and ***EMFCI3*** (corresponding to the FCI incorporating information from all stress indicators, but excluding all vulnerability indicators—this is the DPOR-EMPI index

(continued…)

We next ask which components of demand transmit the impact of shocks to financial conditions to domestic output and economic activity. We decompose domestic demand into private demand and government expenditure which reveals that the growth enhancing effect operates primarily through private domestic demand—both private investment and consumption fall significantly a quarter after domestic financial conditions tighten. By contrast, government spending is statistically decoupled (Table 5). This result provides a potential link between the strength and persistence of the growth-enhancing effect of easier financial conditions and the level of public debt in emerging market economies. In countries with a high-level of public debt, crowding out of private domestic demand may attenuate the growth-enhancing effect, reducing its potency in terms of the size and duration of the growth impulse generated by loosening shocks to financial conditions. This inhibition of the growth-enhancing effect may also be expressed empirically within the framework of our model through the existence of a larger and statistically significant growth-inhibiting effect.

Finally, as mentioned earlier, we examine macro-financial dynamics using conventional time-series models and compare these findings with those derived from our state-space model. First, we use a parsimonious three-variable vector autoregression (VAR) model with EMFCI and GDP growth as endogenous variables and global financial conditions as an exogenous variable. Next, to reconfirm the bi-directional nature of this relationship — particularly the significance of the *growth-inhibiting* link, we apply a panel VAR (PVAR) model which uses country-level information. Global financial conditions are again included as an exogenous covariate in the PVAR model. The impulse responses from the PVAR model show that GDP growth tends to decline after a surprise tightening of financial conditions in emerging economies consistent with a significant *growth-enhancing* link estimated in our state-space model. However, a divergence emerges when examining the responses of EMFCI to changes in EM-GDP. In this case, the response is statistically insignificant and quantitatively smaller, suggesting that the *growth-inhibiting* link observed through our model setup does not manifest itself in VAR- analysis. These findings are consistent across various models (Appendix C). We use several model simulation exercises to shed more light on possible factors driving such differences as reported in Section 4.5.

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 sample of countries, it is of interest to assess the robustness of these aggregate results against the estimated joint dynamics of growth and financial conditions at the individual country-level. While replacing the sample median-annual GDP growth (EMGDP) with the simple (or weighted) average growth or growth quantiles provides some indication of robustness, 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 2000-2019 for each country in our sample. For 15 of the total 18 emerging market economies, 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. The association of global financial conditions with domestic financial conditions and GDP growth

described in Appendix B). Across the median, 10th, and 5th percentiles of GDP growth, both indices exhibit statistically significant predictive content, with the impact on the lower tail (10th and 5th percentiles) being economically meaningful in each case.

was also along the expected lines in a majority of countries, i.e., a tightening in global financial conditions is associated with tighter domestic financial conditions and lower real GDP growth in the near-term. Overall, these results suggest that the estimated dynamics between FCI and GDP growth at the aggregate emerging market economies-level also hold true at the country-level for the significant majority of countries in our sample.[28]

Balance Sheet Conditions and Finance-Growth Interdependence

In this part of our analysis, we delve deeper into the potential mechanisms shaping macro-financial associations at the country level, with particular attention to the role of macroeconomic imbalances. We ask whether certain economic features—specifically, high public debt and current account deficits, the combination that we call a *twin-balance-sheets deficits* or *twin deficits* condition—are associated with the joint existence and significance of the growth-enhancing and growth-inhibiting effects.[29] The growth-enhancing effect is widely prevalent across our sampled emerging market economies, i.e., in 15 out of the 18 countries, whereas the growth-inhibiting effect is prevalent in about 60 percent of our sample of countries and significant in over 40 percent of them. Public and external balance-sheet vulnerabilities are important in many emerging market economies—their fiscal deficits have, at times, been among the highest in the G-20 and their current account deficits are often exacerbated by large energy import bills. We investigate whether these imbalances predispose countries to exhibit both effects and whether, due to increased reliance on external financing to sustain domestic demand, economic growth is more vulnerable to episodes of financial tightening.

As an initial step, we use the median (τ=0.50) quantile regression to explore whether the weak twin-balance-sheets conditions—defined as periods of high public debt and/or weak current account—amplifies the link between domestic financial conditions (EMFCI3) and GDP growth. Results reported in Table 7 confirm such amplification. In Models 1–4, controlling for public debt and/or current account balance increases the absolute size and statistical significance of the coefficient on EMFCI3 in GDP growth regressions (from −0.17 to −0.25), indicating that growth is more vulnerable to financial tightening under weak twin balance sheets conditions. By contrast, the reverse link—GDP growth affecting EMFCI3 (Models 5–8)—shows no comparable amplification, underscoring that the asymmetry lies in the near-term impact of financial tightening on GDP growth. These findings provide the motivation for a more formal, sample-split exercise, where we explicitly compare the finance–growth feedback relationship in countries that have, on average, exhibited weaker fiscal and external sector balance-sheets than the in-sample peer benchmark.

To this end, we split our sample of emerging market economies into subsamples based on a country's relative fiscal and current account performance—both taken as share of GDP—over the sampling period. Specifically, we first calculate the median level of government debt and current account balance across the full country sample for each year of the sampling horizon of 2000 to 2019. Next, these year-wise median values are averaged over 2000–2019 to compute a long-term benchmark value for both fiscal and current account balances. Then, for each country, we compute the average level of government debt and current

[28] Our country-level analysis reported in Table 6 presents few cases of countries where, notwithstanding significant global financial integration, domestic financial conditions appear to be statistically decoupled from shocks to global financial conditions. Earlier studies suggest consideration of a range of factors as relevant in interpreting such a result. The Central Bank of Chile (2020) argues that the regulatory framework, the pension fund system, and the flexible exchange rate regime in the country combine to act as mitigating factors. The first ensures buffers by incentivizing conservative decisions in regulated financial institutions; the second enhances the depth of local capital market; and the third creates an effective shock absorber for external shocks.

[29] We use debt and current-account positions as **indirect proxies** for fiscal space and external funding risk, and not as direct measures of fiscal cyclicality. Hence, the twin deficits amplification is interpreted through a **risk-premium/financing-constraint** channel rather than fixed multiplier assumptions (cf. Jalles et al., 2024).

account balance over the same period. Finally, we compare these country-wise averages with the benchmark values to categorize countries in different groups.

Countries with average government debt levels above the long-term benchmark are classified as high debt (HD) economies, while those below the benchmark are classified as low debt (LD) economies. Countries with an average current account balance above the benchmark are classified as current account surplus (CAS) economies and those with balances lower than the benchmark are classified as current account deficit (CAD) economies. This leads to a four-fold classification of our sampled emerging market economies into: (i) High Debt and Current Account Surplus (HD-CAS); (ii) Low Debt and Current Account Surplus (LD-CAS); (iii) High Debt and Current Account Deficit (HD-CAD); and (iv) Low Debt and Current Account Deficit (LD-CAD) countries. Figure 4 visualizes the distributions relative to the benchmarks and the resulting subgroup splits.

Taking each set of country subsamples, we estimate our empirical model using group-wise median financial conditions and GDP growth. These estimates, reported in Table 8, indicate that the growth-financial conditions feedback loop is stronger when the country's public and external balance-sheets are both constrained, i.e., the HD–CAD configuration—the classic twin-deficits countries—consistently exhibit coexistence of growth-enhancing and growth-inhibiting effects, as do the HD–CAS countries. By contrast, the LD–CAS countries, i.e., those with ample fiscal and external balance sheets space is the only group in which neither effect is statistically significant.[30] The feedback loop being absent from LD-CAS countries is consistent with greater room for counter-cyclical policy (e.g., Jalles et al., 2024).

Finally, we corroborate the above evidence on the role of macroeconomic balances in driving macro-financial interactions in emerging market economies using VAR analysis. Specifically, we use group-wise median financial conditions and growth to estimate impulse responses for country subsamples: **Group A** of HD-CAD countries and **Group B** consisting of all the other countries (i.e., HD-CAS, LD-CAD, LD-CAS). The results show that the growth-enhancing effect—the beneficial impact on near-term growth of an easing of financial conditions—is stronger and lasts for about four quarters for the Group A countries. These findings indicate that the presence of fiscal and current account imbalances tends to amplify the macro-financial linkages in an economy. In contrast, such shocks have neither persistent nor significant impact on Group B countries, indicating that they may not be prone to such vulnerabilities. See Appendix C for VAR results and supporting discussion.

Role of Global Factors

A key question in understanding macro-financial dynamics in emerging market economies is the role of global factors, particularly global financial conditions. To investigate this, we revisit Table 2 to compare our baseline and augmented model specifications. The baseline model shown in panel (1) captures only the dynamic interaction between EMFCI and EMGDP. The augmented specification shown in panel (2) introduces global financial conditions as an exogenous variable that influences the macro-financial associations in Emerging market economies. This adjustment leads to several important findings.

[30] We also considered an alternate sampling criterion by approaching the issue from the perspective of finance-growth relationship within each country. Specifically, we categorize countries based on the presence of a statistically significant growth-inhibiting and growth-enhancing linkages at the country level. Thus, we compare countries experiencing both links with the set of countries exhibiting only the growth-enhancing effect. On average, the former set of countries exhibit higher levels of sovereign debt and current account deficits compared to the latter group. Sample-wise model estimates further confirm that countries with high debt and current account deficits (HD-CAD) are particularly susceptible to prevalence of both growth-enhancing and growth-inhibiting effects. Moreover, coefficients underlying the growth-enhancing and growth-inhibiting linkages are also larger for such countries, suggesting that these countries are constrained by amplified macro-financial dynamics due to the presence of twin-deficits.

First, it leads to an improved model fit as indicated by a reduction in the corrected Akaike Information Criterion (AIC) and an increase in the log-likelihood value. These improvements suggest that global financial conditions are a significant common factor in the domestic macro-financial cycles of emerging market economies. Second, and more importantly, accounting for global financial conditions appears to amplify the estimated growth-inhibiting effect i.e., the feedback loop where a positive growth shock is associated with tighter financial conditions in the near-term which could dampen future growth outcomes. When global financial conditions are included as a covariate, the coefficient linking GDP growth to EMFCI increases by over 37 percent, from 0.35 in the baseline specification to 0.48 in the augmented model.[31]

Thus, incorporating the global financial cycle as an exogenous variable enhances our understanding of the nature of macro-financial dynamics in emerging market economies. Global financial conditions not only impact domestic financial conditions and economic growth directly but also amplify the feedback loop between them.

Model Simulation Exercise

In this section, we explore what could be driving the disparate results between our empirical model and conventional time-series models as discussed earlier. We observe that the growth-enhancing link (EMFCI→GDP) is consistently significant across models, whereas the growth-inhibiting link (GDP→EMFCI) is only significant muted in the state-space model but not in the VAR/PVAR models. Conventional time-series (or panel) VAR models indicate a statistically insignificant response of domestic financial conditions to changes in GDP growth. This difference raises an important question: are we capturing the true associations between financial conditions and GDP growth in emerging market economies by allowing them to interact in a feedback loop?

To answer this question, we conduct a series of simulation exercises on the interaction matrix B, which governs the nature of the associations between the variables in the model (Appendix D). The goal is to determine if allowing for bi-directional feedback between financial conditions and GDP growth brings us closer to capturing the true dynamics of the relationship.

We begin with a model specification which features a fully unconstrained interaction matrix with non-zero and unequal parameter values. This specification allows us to capture the bi-directional associations reflecting the feedback loop. The results are shown in Appendix D, Table D1. For subsequent specifications, we sequentially constrain the variable interaction matrix. Therefore, the second specification corresponds to a unequal diagonal B matrix allowing for non-zero and unequal diagonal values. The third model is specified with an equal diagonal B matrix where model parameters take non-zero but equal diagonal values. Finally, in the last specification, the interaction matrix B is set to an identity matrix implying no interaction between the variables. The results of these simulations reveal that the model fit consistently declines as we constrain the variable associations. This suggests that a fully unconstrained system, permitting bi-directional associations, is the most accurate specification for capturing the true relationship between financial conditions and GDP growth in emerging markets.

[31] To further confirm these dynamics, we examine coefficients across several model specifications in Table 3. In each case, the influence of global financial conditions on domestic macro-financial dynamics is consistent: the coefficient b_{gf} gets amplified, while the b_{fg} coefficient is dampened. Specifically for median GDP Growth, b_{gf} coefficient capturing the effect of EMGDP growth on EMFCI increases from 0.35 to 0.48. In case of mean GDP Growth, it rises from 0.35 to 0.66, while it increases from 0.35 to 3.49 in case of weighted average EMGDP Growth. In all of these specifications, however, the effect of EMFCI on EMGDP growth – b_{fg} - shows no amplification, further supporting the notion that the global financial cycle primarily amplifies the growth-inhibiting link rather than the growth-enhancing link.

Next, we turn our attention to another set of simulation exercises to deepen our understanding of the model, focusing on how the growth-inhibiting link operates. In this exercise, we modify how we model the three variables, namely EMFCI, EMGDP and global financial conditions within our state-space specification. Instead of treating EMGDP as part of the process equation, we consider it as an exogenous covariate while EMFCI and GFC serve as endogenous variables. Results are provided in Appendix D, Table D2. Once we remove GDP from the feedback system and treat it as an exogenous variable, the coefficient for EMGDP on EMFCI becomes statistically insignificant. In other words, in the specification where EMGDP is treated as a covariate, the Cfg coefficient is -0.18 and remains statistically insignificant. This outcome aligns with the findings from alternative time-series models that struggle to capture the growth-inhibiting link.

Conclusions

This paper employs a MARSS model to characterize macro-financial dynamics in emerging market economies. Unlike conventional time-series approaches, this framework illustrates the operation of two distinct drivers, a growth-enhancing effect, wherein easier financial conditions are associated with stronger near-term growth, and a separate growth-inhibiting effect, wherein stronger growth is associated with tighter near-term financial conditions. A sample split indicates that emerging market economies with high public debt and current account deficits display greater this macro-financial feedback more consistently and significantly. Countries with low public debt and strong external balances only display a standard growth-enhancing effect that has previously been identified in the context of advanced economies. Moreover, in emerging market economies, the growth-enhancing effect is shown to operate mainly through private demand, suggesting an emphasis on private-sector credit conditions when conditions tighten.

Accounting for global financial conditions is associated with better model fit and larger estimate of macro-financial feedback. In addition, incorporating information on both stress and vulnerabilities in domestic FCIs aligns with emerging market-specific cyclical features (e.g., higher consumption volatility and exposure to sudden stops) and yields more informative state estimates.

Estimating dynamics in a state-space framework helps counter measurement-error attenuation in observables-based VAR/PVAR models by filtering noisy emerging market economy aggregates (via the Kalman filter). Our estimates remain reduced form: the feedback coefficients capture predictive linkages, not identified fiscal or credit multipliers. A natural next step is a structural or semi-structural design that jointly identifies fiscal and private-credit transmission—allowing multipliers to vary over the cycle—and nests our balance-sheet linkages and twin balance sheets heterogeneity.

Finally, because tightening bites hardest in the lower half of the growth distribution (Table 4), the payoff to countercyclical macroprudential buffers is state-dependent: buffers built in easing phases should be available for release when growth is weak and conditions tighten. As emerging market economies' financial integration deepens, frameworks that jointly track domestic FCIs and global financial conditions indicators, while addressing public-debt and external-balance risks, will be central to stabilizing growth and reducing tail outcomes.

References

Acharya VV, Bhadury, S., and Surti, J. (2025). Financial Conditions and Risks to Growth in Emerging Markets. *Indian Economic Journal*, **73**(1), 18-56.

Acharya VV, Pedersen LH, Philippon T, and Richardson M (2017). “Measuring Systemic Risk.” *Review of Financial Studies*, **30**(1), 2–47.

Acharya, V. V., and Steffen, S. (2015). The “Greatest” Carry Trade Ever? Understanding Eurozone Bank Risks. *Journal of Financial Economics,* **115**(2), 215–236.

Acharya, V. V. and Vij, S. (2024). Regulating Carry Trades: Evidence from Foreign Currency Borrowing of Corporations in India. *Review of Economic Studies*, **92**(4), 2071-2107.

Adrian T, Boyarchenko N, and Giannone D (2019). “Vulnerable growth.” *American Economic Review*, **109**(4), 1263–1289.

Adrian, T., Grinberg, F., Liang, N., Malik, S., and Yu, J. (2022). “The Term Structure of Growth-at-Risk.” *American Economic Journal: Macroeconomics*, **14**(3), 73-131.

Adrian, T., and Liang, N. (2018). “Monetary Policy, Financial Conditions and Financial Stability.” *International Journal of Central Banking,* **14**(1), 283-323.

Afonso A., and Sousa R.M. (2012). “The Macroeconomic of Fiscal Policy.” *Applied Economics*, **44**(34), 4439–4454.

Agnello L., Furceri D., and Sousa R.M. (2013). “How Best to Measure Discretionary Fiscal Policy? Assessing its Impact on Private Spending.” *Economic Modelling*, **34**, 15–24.

Aiyagari S.R., Christiano L.J., and Eichenbaum M. (1992). “The Output, Employment, and Interest Rate of Government Consumption.” *Journal of Monetary Economics*, **30**(1), 73–86.

Akıncı Ö., and Chahrour R. (2018). “Good News is Bad News: Leverage Cycles and Sudden Stops.” *Journal of International Economics*, **114**, 362–375.

Arrigoni S., Bobasu A., and Venditti F. (2022). “Measuring Financial Conditions Using Equal Weights Combination.” *IMF Economic Review*, **70**(4), 668-697.

Barajas A., Choi W.G., Gan K.Z., Guerin P., Mann S., Wang M., and Xu Y. (2021). “Loose Financial Conditions, Rising Leverage, and Risks to Macro-Financial Stability.” *IMF Working Paper 2021/222*, International Monetary Fund.

Baxter M., and King R.G. (1993). “Fiscal Policy in General Equilibrium.” *American Economic Review*, **83**(3), 315–334.

Bekaert G., Harvey C.R., Lundblad C.T., and Siegel S. (2011). “What Segments Equity Markets?” *Review of Financial Studies*, **24**(12), 3841–3890.

Berger, A. N., and Udell, G. F. (2004). The Institutional Memory Hypothesis and the Procyclicality of Bank Lending Behavior. *Journal of Financial Intermediation*, **13**(4), 458–495.

Bianchi J. (2011). “Overborrowing and Systemic Externalities in the Business Cycle.” *American Economic Review*, **101**(7), 3400–3426.

Bianchi J., and Mendoza E.G. (2018). “Optimal Time-Consistent Macroprudential Policy.” *Journal of Political Economy*, **126**(2), 588–634.

Bianchi J., and Mendoza E.G. (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., and Perotti R. (2002). "An Empirical Characterization of the Dynamic of Changes in Government Spending and Taxes on Output." *Quarterly Journal of economics*, **117**(4), 1329–1368.

Brownlees C., and Engle R.F. (2017). "SRISK: A Conditional Capital Shortfall Measure of Systemic Risk." *Review of Financial Studies*, **30**(1), 48–79.

Brunnermeier M.K., Sannikov Y. (2014). "A Macroeconomic Model With a Financial Sector." *American Economic Review*, **104**(2), 379–421.

Bruno V., and Shin H.S. (2020). "Currency Depreciation and Emerging Market Corporate Distress." *Management Science*, **66**(5), 1935–1961.

Central Bank of Chile (2020). "External Financial Conditions and their Impact on Local Markets." *Financial Stability Report*, **2**, Chapter IV, 54-63.

Christiano L.J., and Eichenbaum M. (1992). "Current Real-Business-Cycle Theories and Aggregate Labor-Market Fluctuations." *American Economic Review*, **82**(3), 430–450.

Claessens S., Dell'Ariccia G., Igan D., and Laeven L. (2010). "Cross-country Experiences and Policy Implications From the Global Financial Crisis." *Economic Policy*, **25**(62), 267–293.

Claessens S., Köse M.A. (2013). "Financial Crises: Review and Evidence." *Central Bank Review*, **13**(3).

Claessens S., and Köse M.A. (2018). "Frontiers of Macrofinancial Linkages." *BIS Paper No. 95*.

Claessens S., Köse M.A., and Terrones M.E. (2010). "The Global Financial Crisis: How Similar? How Different? How Costly?" *Journal of Asian Economics*, **21**(3), 247–264.

Danielsson J., James K.R., Valenzuela M., and Zer I. (2016). "Model Risk of Risk Models." *Journal of Financial Stability*, **23**, 79–91.

Davis J.S., Devereux M.B., and 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., and Vandenbussche J. (2012). "Policies for Macrofinancial Stability: How to Deal with Credit Booms." *IMF Staff Discussion Note*, **12**(06).

Dell'Ariccia G., and Marquez R. (2013). "Interest Rates and the Bank Risk-taking Channel." *Annual Review of Finance and Economics*, **5**(1), 123–141.

Doz C., Giannone D., and Reichlin L. (2011). "A Two-Step Estimator for Large Approximate Dynamic Factor Models Based on Kalman Filtering." *Journal of Econometrics*, **164**(1), 188–205.

Dumitrescu E.I., and Hurlin C. (2012). "Testing for Granger Non-causality in Heterogeneous Panels." *Economic Modelling*, **29**(4), 1450–1460.

Eichengreen B., and Gupta P. (2016). "Managing Sudden Stops." *World Bank Policy Research Working Paper No. 7639*.

Eichengreen B., Rose A., and Wyplosz C. (1996). "Contagious Currency Crises: First Tests." *Scandinavian Journal of Economics*, **98**(4), 463–484.

Evanoff D.D., Kaufman G.G., and Malliaris A.G. (2012). *New Perspectives on Asset Price Bubbles*. Oxford University Press.

Foley D.K. (1987). "Liquidity-Profit Rate Cycles in a Capitalist Economy." *Journal of Economic Behavior & Organization*, **8**(3), 363–376.

Forni M., Hallin M., Lippi M., and Reichlin L. (2000). "The Generalized Dynamic-Factor Model: Identification and Estimation." *Review of Economics and statistics*, **82**(4), 540–554.

Frost T.M., Carpenter S.R., Ives A.R., and Kratz T.K. (1995). "Species Compensation and Complementarity in Ecosystem Function." in *Linking Species and Ecosystems*, pp. 224–239. Springer.

Funashima Y., and Ohtsuka Y. (2019). "Spatial Crowding-out and Crowding-in of Government Spending on the Private Sector in Japan." *Regional Science and Urban Economics*, **75**, 35–48.

Furceri D., and Sousa R.M. (2011). "The Impact of Government Spending on the Private Sector: Crowding-out versus Crowding-in." *Kyklos*, **64**(4), 516–533.

Gennaioli, N., Shleifer, A., and Vishny, R. (2012). "Neglected Risks, Financial Innovation, and Financial Fragility. *Journal of Financial Economics,* **104**(3), 452–468.

Giannone D., Reichlin L., and Small D. (2008). "Nowcasting: The Real-Time Informational Content of Macroeconomic Data." *Journal of Monetary Economics*, **55**(4), 665–676.

Girton L., and Roper D. (1977). "A Monetary Model of Exchange Market Pressure Applied to the Postwar Canadian Experience." *American Economic Review*, **67**(4), 537–548.

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

Greenwood R., Hanson S.G., Shleifer A., and Sørensen J.A. (2022). "Predictable Financial Crises." *Journal of Finance*, **77**(2), 863–921.

Gross M. (2022). "Beautiful Cycles: A Theory and a Model Implying a Curious Role for Interest." *Economic Modelling*, **106**, 105678. ISSN 0264-9993.

Guttentag J., and Herring R. (1984). "Credit Rationing and Financial Disorder." *Journal of Finance*, **39**(5), 1359–1382.

Hampton S.E., Holmes E.E., Scheef L.P., Scheuerell M.D., Katz S.L., Pendleton D.E., and Ward E.J. (2013). "Quantifying of Abiotic and Biotic Drivers on Community Dynamics with Multivariate Autoregressive (MAR) Models." *Ecology*, **94**(12), 2663–2669.

Ives A.R. (1995). "Measuring Resilience in Stochastic Systems." *Ecological Monographs*, **65**(2), 217–233.

Ives A.R., Carpenter S.R., and Dennis B. (1999). "Community Interaction Webs and Zooplankton Responses to Planktivory Manipulations." *Ecology*, **80**(4), 1405–1421.

Ives A.R., Dennis B., Cottingham K.L., and Carpenter S.R. (2003). "Estimating Community Stability and Ecological from Time-series Data." *Ecological Monographs*, **73**(2), 301–330.

Jalles, J. T., Kiendrebeogo, Y., Lam, R., and Piazza, R. (2024). *Revisiting the Countercyclicality of Fiscal Policy*. Empirical Economics, **67**, 877–914.

Jarsulic M. (1989). "Endogenous Credit and Endogenous Business Cycles." *Journal of Post Keynesian Economics*, **12**(1), 35–48.

Jeanne O., and Korinek A. (2010). "Excessive Volatility in Capital Flows: A Pigouvian Taxation Approach." *American Economic Review*, **100**(2), 403–407.

Jordà O., Schularick M., and Taylor A.M. (2013). "When Credit Bites Back." *Journal of Money, Credit and Banking*, **45**(s2), 3–28.

Joyce J.P., and Nabar M. (2009). "Sudden Stops, Banking Crises and Investment Collapses in Emerging Markets." *Journal of Development Economics*, **90**(2), 314–322.

Korinek A., and Mendoza E.G. (2014). "From Sudden Stops to Fisherian Deflation: Quantitative Theory and Policy." *Annual Review of Economics*, **6**(1), 299–332.

Krishnamurthy A., and Muir T. (2025). “How Credit Cycles Across a Financial Crisis.” *Journal of Finance*, **53**(3), 1339-1378.

Levy-Yeyati E., and 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 E.G. (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 E.G. (2010). “Sudden Stops, Financial Crises, and Leverage.” *American Economic Review*, **100**(5), 1941–1966.

Mian A., Sufi A., and Verner E. (2017). “Household Debt and Business Cycles Worldwide.” *Quarterly Journal of Economics*, **132**(4), 1755–1817.

Mian A., Sufi A., and Verner E, (2020). “How Does Credit Supply Expansion Affect the Real Economy? The Productive Capacity and Household Demand Channels.” *Journal of Finance*, **75**(2), 949–994.

Miranda-Agrippino S., and Rey H. (2022). “The Global Financial Cycle.” in *Handbook of International Economics*,” Volume 6, 1–43. Elsevier.

Nikolaidi M., and Stockhammer E. (2018). “Minsky Models: A Structured Survey.” *Analytical Political Economy*, pp. 175–205.

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., and Taylor A.M. (2004). *Global Capital Markets: Integration, Crisis, and Growth*. Cambridge University Press.

Paine R.T. (1980). “Food Webs: Linkage, Interaction Strength and Community Infrastructure.” *Journal of Animal Ecology*, **49**(3), 667–685.

Park J.K., and Meng X. (2024). “Crowding Out or Crowding In? Reevaluating the Effect of Government Spending on Private Economic Activities.” *International Review of Economics and Finance*, **89**, 102–117.

Rajan R.G. (1994). “Why Bank Credit Policies Fluctuate: A Theory and Some Evidence.” *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., and Travlos N.G. (1990). “Ownership Structure, Deregulation, and Bank Risk Taking.” *Journal of Finance*, **45**(2), 643–654.

Scherbina M.A. (2013). *Asset Price Bubbles: A Selective Survey*. International Monetary Fund.

Schularick M., and Taylor A.M. (2012). “Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870–2008.” *American Economic Review*, **102**(2), 1029– 1061.

Semmler W. (1987). “A Macroeconomic Limit Cycle with Financial Perturbations.” *Journal of Economic Behavior and Organization*, **8**(3), 469–495.

Sufi A., and Taylor A.M. (2022). “Financial Crises: A Survey.” *Handbook of International Economics*, Volume 6, 291–340.

Surti J., Alter A., Brandao-Marques L., Chen Q., Elekdag S., Huston B., Khadarina O., Miao H., Monroe W., and Zhu L. (2016). “The Growing Importance of Financial Spillovers from Emerging Markets.” *IMF Global Financial Stability Report*, April, 57–86.

Surti J., Katagiri M., Lafarguette R., Malik S., and Seneviratne D. (2017). “Financial Conditions and Growth-at-Risk.” *IMF Global Financial Stability Report*, April, 91–118.

Taylor L., and O’Connell S.A. (1985). “A Minsky Crisis.” *Quarterly Journal of Economics*, **100**(Supplement), 871–885.

Tilman D. (1996). “Biodiversity: Population versus Ecosystem Stability.” *Ecology*, **77**(2), 350–363.

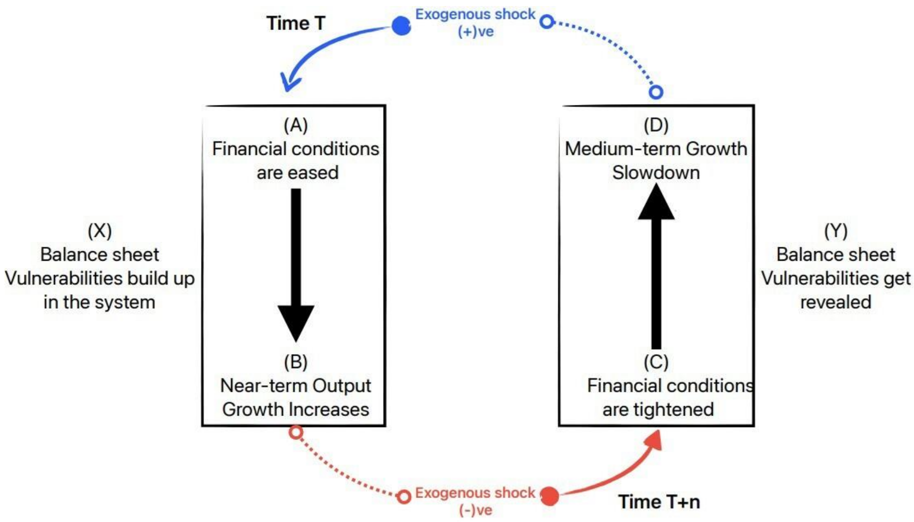
Torre V. (1977). “Existence of Limit Cycles and Control in Complete Keynesian System by Theory of Bifurcations.” *Econometrica*, **45**(6), 1457–1466.

Williamson O.E. (1963). “Managerial Discretion and Business Behavior.” *American Economic Review*, **53**(5), 1032–1057.

Tables and Figures

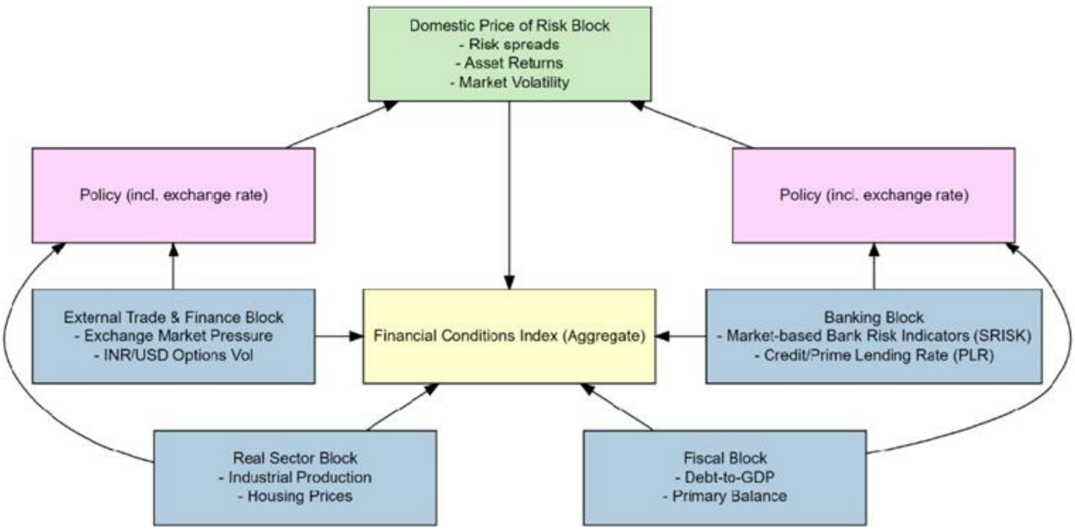
Figures

Figure 1. Macro-financial Associations in Emerging Markets - Analytical Framework



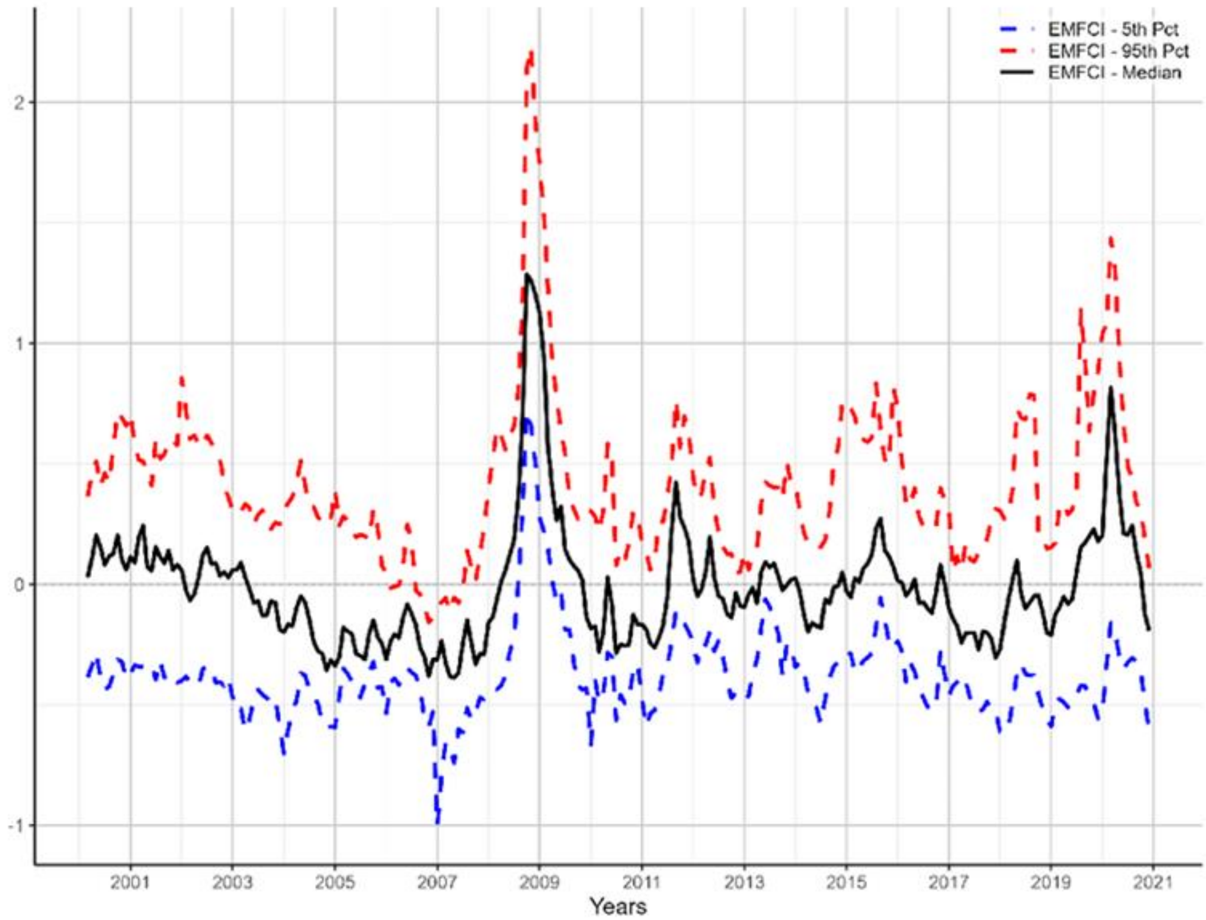
Note: The above flowchart depicts the analytical framework used for analyzing macro-financial associations in emerging economies.

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 lie the aggregate financial conditions which encompass fast-moving stress indicators (e.g., risk spreads, asset price returns) and indicators reflecting the gradually accumulating vulnerabilities (e.g., S-risk, Debt-to-GDP). Additionally, sector-specific indicators are clubbed under blocks which may directly or indirectly impact financial conditions in the economy. These indicators enable the capture of the evolving dynamics of financial conditions. While real sector conditions are proxied by the B-L block can be expected to impact domestic financial conditions in the analysis, we show that our results are robust to excluding this block when constructing our country-specific and aggregate EM financial conditions indices.

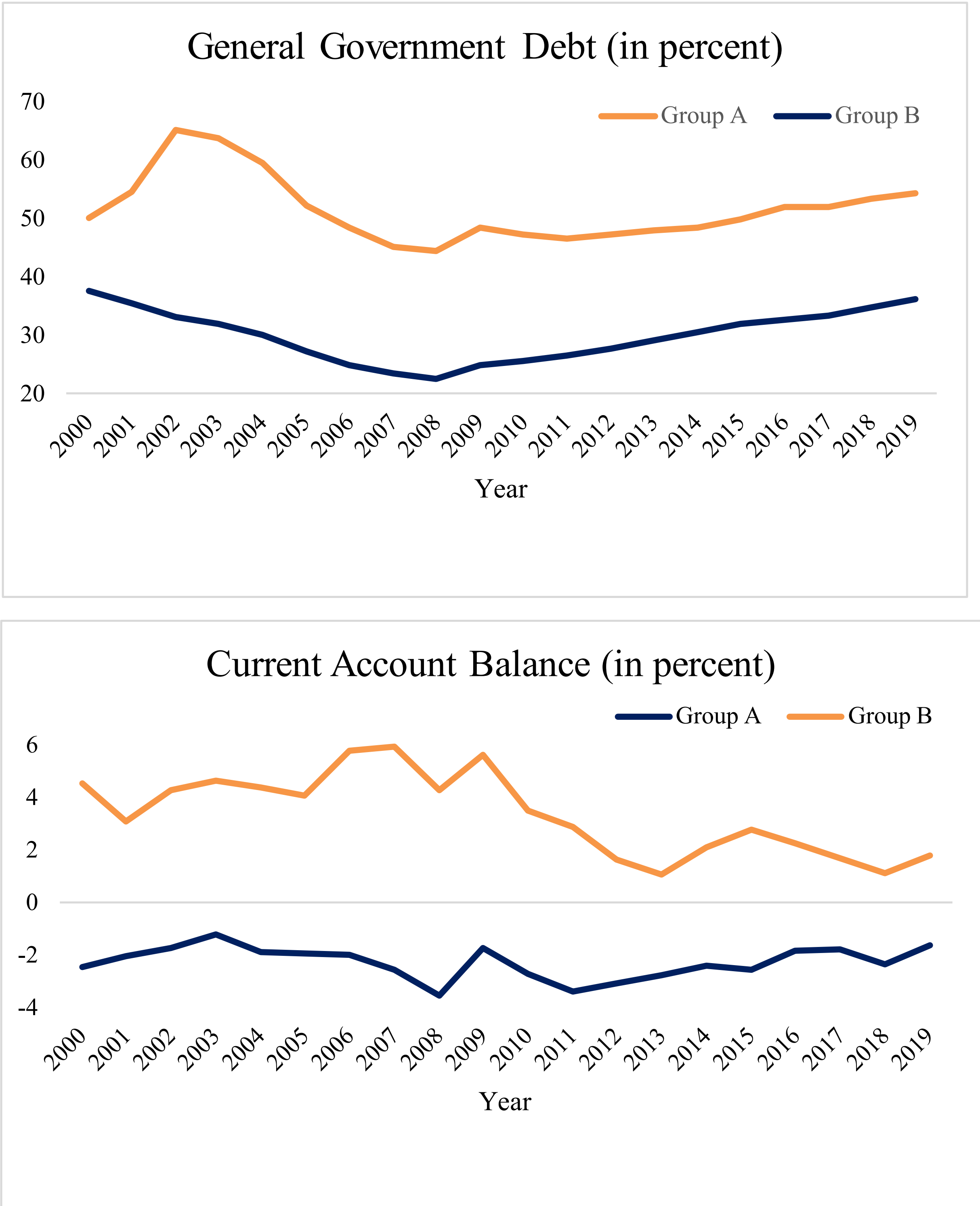
Figure 3. Financial Conditions Index (FCI) for Emerging Economies



Source: Authors' calculations.

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. The panel extends using inputs available through 2021 and note main MARSS estimates span from 2000Q1 to 2019Q4.

Figure 4. Fiscal and Current Account Balance



Source: Authors' calculations.
Note: Each point is a country's 2000–2019 average (percent of GDP). Top panel: government debt-to-GDP; bottom panel: current account balance-to-GDP. Countries are classified relative to these benchmarks as High Debt (HD) vs. Low Debt (LD) and Current Account Surplus (CAS) vs. Current Account Deficit (CAD). The four quadrants—HD–CAD (twin-deficit), HD–CAS, LD–CAD, and LD–CAS—are the subgroups used in Section 4.3.

Tables

Table 1. Financial Conditions Index: Data and Variable Construction

Variable Name	Description	Countries	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 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 (banking sector)	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	NYU V-Lab
PLR	Corporate sector prime lending rate	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	Bloomberg
OptionVol3m	Implied volatility of USD vs EM currency (3-month options)	BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA	Bloomberg
Term Spread	10Y/5Y government bond yield minus 91-day T-bill yield (as available)	BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA	Bloomberg
Corporate Spread	3-month CEMBI corporate yield minus 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	3-month interbank rate minus 91-day 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 market pressure index (FX intervention or ER movement)	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	IMF
Debt-to-GDP	Gross general government debt (percent of GDP)	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	IMF
Primary Balance	General government primary balance (percent of GDP)	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	IMF
Real-estate prices	Residential and commercial property price indices	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	BIS
Industrial production	Industrial production index (economic activity)	ARG, BRA, CHI, CHN, COL, CZE, INDI, INDO, KOR, MAL, MEX, PHI, POL, RUS, SLO, SAF, THA, TUR	IMF

Notes: (1) Country codes: ARG = Argentina; BRA = Brazil; CHI = Chile; CHN = China; COL = Colombia; CZE = Czechia; INDI = India; INDO = Indonesia; KOR = Korea; MAL = Malaysia; MEX = Mexico; PHI = Philippines; POL = Poland; RUS = Russia; SLO = Slovakia; SAF = South Africa; THA = Thailand; TUR = Türkiye.

(2) The above table provides a list of variables used for constructing country-level FCIs using the DFM framework described in (8) and (9).

Table 2 (a). Results: Estimated Model Coefficients with and without Covariates

	Baseline	Augmented
Model Coefficients	**(1)**	**(2)**
B_{ff}	0.91***	0.85***
	(0.10)	(0.10)
B_{fg}	-0.46***	-0.41***
	(0.06)	(0.07)
B_{gf}	0.20**	0.27***
	(0.09)	(0.09)
B_{gg}	0.56***	0.51***
	(0.07)	(0.07)
C_{ff}	–	0.18**
	–	(0.09)
C_{fg}	–	-0.14**
	–	(0.06)
AICc	247.29	242.50
Log-likelihood	-112.91	-108.19
Interaction Period	2000-2019	2000-2019
Covariate Period	–	2000-2019

Source: Authors' calculations.
Note: The above table shows the maximum likelihood estimates for the interaction matrix of the MARSS model described in equation (5)-(7). bps = 100×Bfg×sd(y). Estimated standard errors are shown in parentheses. We invert Rey's GFC (higher = tighter), a positive C_{ff} means tighter global conditions tighter global cycles tighten EMFCI, while a negative C_{fg} means tighter global conditions lower EM GDP growth.

Table 2 (b). Results: Estimated Model Coefficients with Covariates

	Augmented
Model Coefficients	**(EMFCI3)**
B_{ff}	0.79***
	(0.09)
B_{fg}	-0.20***
	(0.06)
B_{gf}	0.19**
	(0.09)
B_{gg}	0.62***
	(0.08)
C_{ff}	0.14
	(0.09)
C_{fg}	-0.24***
	(0.07)
AICc	272.92
Log-likelihood	-123.40
Interaction Period	2000-2019
Covariate Period	2000-2019

Source: Authors' calculations.
Note: The above table shows the maximum likelihood estimates for the interaction matrix of the MARSS model described in equation (5)- (7). The model is estimated at the aggregate EM-level with an alternative measure of EM level FCI measure (EMFCI) that is devoid of real activity. Estimated standard errors are shown in parentheses. Positive C_{ff} means tighter global conditions tighter GFC tighten EMFCI, while a C_{fg} negative means tighter GFC lower EM GDP growth.

Table 3 (a). 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	225.60	272.90
Log-likelihood	-108.19	-96.1	-99.74	-123.39
Interaction Period	2000-2019	2000-2019	2000-2019	2000-2019
Covariate Period	2000-2019	2000-2019	2000-2019	2000-2019

Source: Authors' calculations.

Note: The above table shows the maximum likelihood estimates for the interaction matrix of the MARSS model described in equation (5)-(7). The model is estimated at the aggregate EM-level using different measures of annual EM GDP growth. Positive C_{ff} means tighter global conditions tighter GFC tighten EMFCI, while a C_{fg} negative means tighter GFC lower EM GDP growth.

Table 3 (b). 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}	0.80***	0.85***	0.82***	0.83***
	(0.09)	(0.04)	(0.04)	(0.09)
B_{fg}	-0.20***	-0.37***	-0.14**	-0.16**
	(0.06)	(0.08)	(0.07)	(0.07)
B_{gf}	0.19**	0.06**	0.00	0.28***
	(0.09)	(0.03)	(0.04)	(0.09)
B_{gg}	0.62***	0.63***	0.85***	0.61***
	(0.08)	(0.07)	(0.06)	(0.09)
C_{ff}	0.14	0.02	0.01	0.18**
	(0.09)	(0.02)	(0.02)	(0.08)
C_{fg}	-0.24***	-0.21***	-0.07**	-0.23***
	(0.07)	(0.04)	(0.03)	(0.08)
AICc	272.92	180.36	121.09	289.52
Log-likelihood	-123.40	-122.24	-73.61	-131.70
Interaction Period	2000-2019	2000-2019	2000-2019	2000-2019
Covariate Period	2000-2019	2000-2019	2000-2019	2000-2019

Source: Authors' calculations.

Note: The above table shows the maximum likelihood estimates for the interaction matrix of the MARSS model described in equation. The model is estimated at the aggregate EM-level with an alternative measure of EM level FCI measure (EMFCI) that is devoid of real activity. Estimated standard errors are shown in parentheses. Positive C_{ff} means tighter global conditions tighter GFC tighten EMFCI, while a C_{fg} negative means tighter GFC lower EM GDP growth.

Table 4 (a). 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	2000-2019	2000-2019	2000-2019	2000-2019

Source: Authors' calculations.
Note: The above table shows the maximum likelihood estimates for the interaction matrix of the MARSS model described in equation (5)-(7). The model is estimated at the aggregate EM-level using different quantiles for annual EM GDP growth. Positive C_{ff} means tighter global conditions tighter GFC tighten EMFCI, while a C_{fg} negative means tighter GFC lower EM GDP growth.

Table 4 (b). 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}	0.79***	0.80***	0.95***	0.77***	0.74***
	(0.09)	(0.09)	(0.06)	(0.09)	(0.09)
B_{fg}	-0.20***	-0.75**	-0.51**	-0.05	0.00
	(0.06)	(0.31)	(0.16)	(0.07)	(0.07)
B_{gf}	0.19**	0.04**	0.04**	0.17	0.19
	(0.07)	(0.02)	(0.02)	(0.09)	(0.10)
B_{gg}	0.62***	0.65***	0.64***	0.62***	0.61***
	(0.08)	(0.08)	(0.07)	(0.12)	(0.12)
C_{ff}	0.14	0.04	0.03	0.15	0.18
	(0.09)	(0.02)	(0.03)	(0.09)	(0.10)
C_{fg}	-0.24***	-0.32***	-0.35***	-0.25**	-0.27**
	(0.07)	(0.10)	(0.08)	(0.10)	(0.11)
AICc	272.92	120.11	121.69	309.07	304.50
Log-likelihood	-123.40	-46.99	-47.78	-141.47	-139.19
Interaction Period	2000-2019	2000-2019	2000-2019	2000-2019	2000-2019
Covariate period	2000-2019	2000-2019	2000-2019	2000-2019	2000-2019

Source: Authors' calculations.
Note: The above table shows the maximum likelihood estimates for the interaction matrix of the MARSS model described in equation. The model is estimated at the aggregate EM-level with an alternative measure of EM level FCI measure (EMFCI) that is devoid of real activity. Positive C_{ff} means tighter global conditions tighter GFC tighten EMFCI, while a C_{fg} negative means tighter GFC lower EM GDP growth.

Table 5. Results: Finance-Growth Feedback by Demand Component

Factors	Bfg	Bgf	Interpretation
GDP	-0.20***	0.19**	Tightening reduces GDP; modest feedback to tighter conditions
Investment	-0.14**	0.20**	Tightening reduces investment; strong bidirectional link
Consumption	-0.19**	0.18*	Tightening reduces consumption; weaker feedback
Government	0.13 (ns)	0.16 (ns)	No reliable cyclical link; possibly counter-cyclical

Note: Entries report coefficients from the EM-level multivariate state-space model's interaction matrix. Bfg is the effect of a one-sd tightening in EM financial conditions (↑EMFCI) on next-quarter growth of the listed component; Bgf is the reverse effect of that component's growth on next-quarter EMFCI. Negative Bfg means tighter conditions reduce the component; positive Bgf means stronger activity tightens conditions. "ns" = not significant, stars denote significance; * p<0.10, ** p<0.05, *** p<0.01.

Table 6. Summary Results: Sign Test

	Growth-enhancing Effect: B_{fg}	Growth-inhibiting 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
Countries without the expected sign	Colombia, Russia and Thailand	China, Mexico, Russia and Thailand	Brazil, Chile, China, Colombia, Czech, Indonesia, Poland and Türkiye	Philippines and Russia
Total # countries	18	18	18	18

Source: Authors' calculations.

Note: The above table shows a summary of results based on estimating the MARSS model described in equation (5)-(7) at the individual country-level for all Emerging market economies in our data sample. The results are based on inference drawn using a standard 5 percent level of significance.

Table 7. Median Quantile Regressions: Financial Conditions, Growth, and Macro-imbalances

Model	Dep. Var.	Key Explanatory Var.	Coefficient (p-value)	Controls	Interpretation
1	GDP	EMFCI3 (-1)	-0.17 (0.06)	None	Mildly negative, marginal significance
2	GDP	EMFCI3 (-1)	-0.23 (0.02)	CAB	Stronger negative effect when CAB included
3	GDP	EMFCI3 (-1)	-0.23 (0.02)	DEBT	Stronger negative effect when Debt included
4	GDP	EMFCI3 (-1)	-0.25 (0.01)	Debt + CAB	Largest negative effect, significant
5	EMFCI	GDP (-1)	0.11 (0.05)	None	GDP increases → tighter financial conditions
6	EMFCI	GDP (-1)	0.12 (0.08)	Debt	Similar effect magnitude
7	EMFCI	GDP (-1)	0.12 (0.04)	CAB	Similar effect magnitude
8	EMFCI	GDP (-1)	0.11 (0.15)	Debt + CAB	Similar effect magnitude

Source: Authors' calculations.

Note: EMFCI3 is the EM financial-conditions index that excludes real-activity variables, demeaned and standardized; higher values denote tighter conditions. Entries are τ=0.50 (median) quantile estimates; standard controls are listed per model. These specifications condition on Debt/CAB levels (no interactions); they motivate, but do not identify, amplification—hence the subgroup analysis that follows.

Table 8. Median Finance-Growth Feedback by Debt and External Balance Subgroups

Scenario	Subgroup	B_{fg} (EMFCI → GDP)	B_{gf} (GDP → EMFCI)
HD vs. LD	HD	−0.47***	0.30***
	LD	−0.27***	0.22***
CAD vs. CAS	CAD	−0.37***	0.31***
	CAS	−0.44***	0.30***
HD–CAS vs. LD–CAD	HD–CAS	−0.44***	0.22***
	LD–CAD	−0.24***	0.26***
HD–CAD vs. LD–CAS	HD–CAD	−0.31***	0.33***
	LD–CAS	−0.02 (ns)	0.12 (ns)

Notes: The table reports median panel estimates of the finance–growth relationship across country subgroups, with B_{fg} denoting the effect of domestic financial conditions on GDP growth, and B_{gf} the reverse link. Asterisks denote statistical significance (*** $p < 0.01$); "ns" indicates non-significance at conventional level.

(1) Debt classification is based on the 2000–2019 average debt-to-GDP ratio relative to the cross-country median; current account classification uses the analogous rule for the average CAB-to-GDP ratio.

(2) EMFCI3 is the Emerging Market Financial Conditions Index, demeaned and standardized at the country level.

(3) The table omits intercepts and control variables for brevity; full regression outputs are available upon request.

Appendix

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 (λ1,t, ..., λn,t) is driven by a vector of r unobserved dynamic factors $(f_{1t}, \dots, f_{rt})$, as well as some series-specific features, such as measurement errors, captured by idiosyncratic errors $(\varepsilon_{1t}, \dots, \varepsilon_{nt})$. Empirically, the DFM can be summarized in the following equation:

$$\lambda_{i,t} = \gamma_i F_t + \varepsilon_{i,t}; i = 1, \dots, n; t = 1, \dots, T \qquad \text{(A1)}$$

where $(\gamma_{1t}, \dots, \gamma_{rt})$ is an r—dimensional vector of factor loadings. 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:

$$\varepsilon_{i,t} = \alpha_i \varepsilon_{i,t-1} + e_{i,t}; e_{i,t} \sim iidN(0, \sigma_i^2); \mathbb{E}(\sigma_{i,s}, \sigma_{j,t}) = 0, i \neq j \qquad \text{(A2)}$$

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

$$X_t = \Gamma F_t + \Pi_t \qquad \text{(A3)}$$

where $X_t = (\lambda_{1,t}, \dots, \lambda_{n,t})'$; $X_t = (\varepsilon_{1,t}, \dots, \varepsilon_{n,t})'$; and $\Gamma = (\gamma_1, \dots, \gamma_r)$. The dynamic behavior of the common factors is modelled as an AR(1) process:

$$F_t = AF_{t-1} + Bu_t \qquad \text{(A4)}$$

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 model parameters. The algorithm is initialized 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 initialization, given that principal components are reliable estimates of the common factors. For example, let S be a sample correlation matrix of a given dataset:

$$S = \frac{1}{T} \sum_{i=1}^{T} X_t X_t' \qquad \text{(A5)}$$

Then, the *r* largest principal components are extracted from the sample correlation matrix. Let *D* be the *r* × *r* diagonal matrix with diagonal elements given by the largest *r* eigenvalues of *S*. Let *V* be the *n* × *r* matrix of corresponding eigenvectors such that the normalization gives *V 'V* = *Ir*. The common factors can be approximated by:

$$\tilde{F} = V' X_t \qquad \text{(A6)}$$

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:

$$\hat{\Gamma} = \Sigma_t X_t \widetilde{F}_t' \left(\widetilde{F}_t \widetilde{F}_t'\right)^{-1} \quad \text{(A7)}$$

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

$$\widehat{\Pi} = diag(S - VDV) \quad \text{(A8)}$$

The dynamic factor equation parameters, A and B, can be estimated from a VAR along with the common factors $\widetilde{F}_t$ where $F_t = AF_{t-1} + Bu_t$. These estimates $\hat{\Gamma}, \widehat{\Pi}, \hat{A}, \hat{B}$, 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 synthetic understanding of the cost and stability of financing for economic activity. Financial stress indicators tend to co-move with actual stress in the system so that they rise and fall as financial stress in the system increases or decreases. Vulnerability indicators accumulate slowly in a shock-free environment, and once they breach a threshold, amplify the impact of adverse exogenous shocks on the economy. Similar to Krishnamurthy and Muir (2025), 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 sample of emerging market economies. We then 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 synthetic yet comprehensive financial conditions index for emerging market economies.

Informational Contribution of Index Constituents of Financial Stress

The financial stress measures are constructed using a sequential approach, incorporating various indicators to capture different aspects of stress. One such block of measures is the domestic *price of risk (DPOR)*, which includes term spreads, sovereign spreads, risk spreads, and asset returns and volatility relevant to costs of funding economic activity in key sectors of the economy. Increasing financial stress is reflected in rising risk spreads and volatility, as well as in falling asset returns.

External risk factors circumscribe global financing conditions and the real channel of terms-of-trade and commodities prices. A second block or measure of indicators, denoted ***DPOR-EXT*** (DPOR-External) expands on the DPOR block by including an additional indicator, the implied option volatility of the domestic currency vis-a-vis the US dollar. An extension of DPOR-EXT can also be developed to provide a more comprehensive view of external sector risk indicators in assessing overall domestic financial stress. The ***DPOR-EMPI*** includes all DPOR-EXT indicators plus a measure of the exchange rate market pressure, providing a better understanding of the interplay between exchange rates and overall market conditions. It is also the basis for constructing ***EMFCI3*** To further enhance the set of information relevant to near-term financial stress, the ***DPOR-MF*** (DPOR-Macro-Financial) index adds real sector indicators, such as the industrial production index (IPI) and housing prices to DPOR-EMPI.

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 measure is the ***DPOR-AGG*** (DPOR-Aggregate) index, which combines information on banking indicators, such as S-Risk and the prime lending rate, with the block of indicators that constitute the DPOR-EMPI index. This augmented index provides further insights into vulnerabilities that may develop in the banking sector and their impact on overall financial conditions.

The ***DPOR-AGG-FISC*** index integrates the indicators in DPOR-AGG with fiscal metrics, such as the general government balance and the public debt-to-GDP ratio. By incorporating fiscal variables, this index highlights the interplay between financial vulnerabilities and the fiscal health of the economy. Separately, the ***DPOR-AGG-BAL*** index combines the indicators in DPOR-AGG with a balance-sheet leverage metric, credit growth. This index, like DPOR-AGG, offers valuable insights into vulnerabilities stemming from the current state of the domestic credit cycle.

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 and is the basis for constructing ***EMFCI1***.

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 Emerging market economies 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 alternate FCI measures are assessed over one-quarter ahead horizon across all countries in our sample.[32]

The results obtained from the above forecast exercise above are presented below. The table below 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 emerging market economies 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 Emerging market economies, underscoring the significance of incorporating a comprehensive assessment of both stress and vulnerabilities in forecasting GDP growth.

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

Table B1. Country-wise Out-of-Sample Root Mean Squared Error (RMSE)

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

Source: Authors' calculations.
Note: Countries in column one of the table are: ARG=Argentina; BRA=Brazil; CHI=Chile; CHN=China; COL=Colombia; CZE=Czech Republic; INDI=India; INDO=Indonesia; KOR=Korea; MAL=Malaysia; MEX=Mexico; PHI=Philippines; POL=Poland; RUS=Russia; SLO=Slovak Republic; SAF=South Africa; THA=Thailand; TUR=Türkiye.

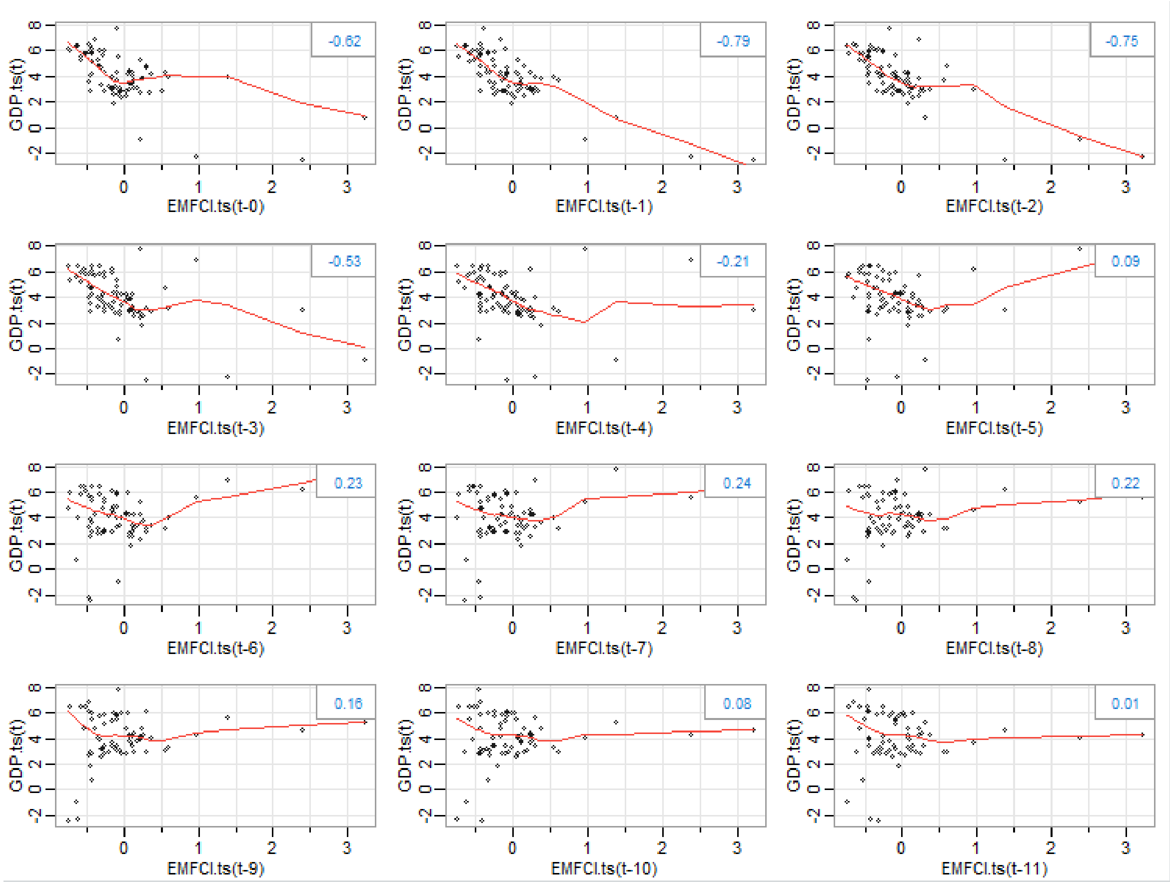
C. Macro-financial Interaction in Emerging Market Economies—Comparison with Alternate Models

This section provides a comparative analysis of macro-financial associations in Emerging market economies as seen from the state-space model used in the paper against some comparative time-series and panel data regression models.

Time-series Evidence

The figure shown below provides a graphical representation of the relationship between GDP growth and FCI in emerging market economies, systematically arranged across different time lags of FCI.

Figure C1. Lead-lag Correlation between EM GDP and FCI

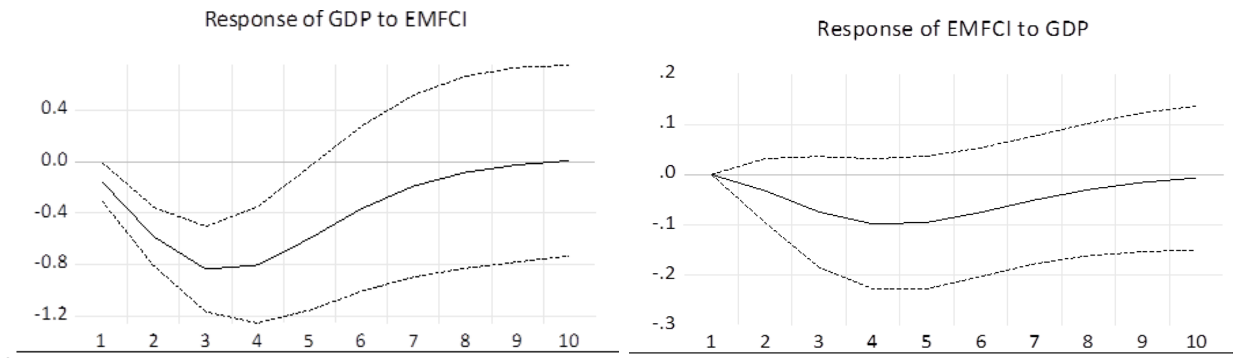


Note: The above figure shows the relationship between GDP growth and financial conditions in emerging market economies. Median-GDP growth and median-FCI for emerging market economies are plotted on the *vertical* and *horizontal* axis, respectively with each panel representing the relation between GDP and lagged values of FCI. For each pair plot, the solid red line shows the line of best fit obtained from *loess* regression, while the correlation coefficient is provided in the upper right-hand corner.

By designating EMGDP as the leading data series and specifying lagged EMFCI, this sheds light on the underlying dynamics of the system. We observe a robust and statistically significant correlation coefficient of -0.79, when one-period lagged financial conditions in emerging market economies are considered. The negative correlation indicates a strong signal in the data signifying the influence of tight financial conditions on subsequent growth outcomes in emerging market economies and the significant negative correlation over four lags of EMFCI is indicative of the persistence of this effect.

Next, we estimate a bivariate, vector autoregression (VAR) model to better understand the dynamics of the system. We use EMFCI and EMGDP as endogenous variables in the estimated VAR. Global financial conditions are taken as an exogenous variable while the model is identified using a Cholesky identification scheme. The estimated impulse responses shown below reveal that GDP growth falls in response to a surprise tightening of financial conditions (left panel) while financial conditions tend to loosen in response to a positive growth shock (right panel). However, the latter response is much softer and statistically insignificant whereas the response of GDP growth to a financial conditions shock is highly and persistently significant.

Figure C2. GDP Growth and Financial Conditions in VAR model – Impulse Responses Analysis



Source: Authors' calculations.
Note: The above figure plots the impulse responses obtained from a three-variable VAR model containing global financial conditions, EMFCI and EMGDP and identified using a Cholesky identification scheme. The left panel showsthe response of EMGDP growth to a one standard deviation (sd) shock to EMFCI while the right panel shows the response of EMFCI to EMGDP shock. The solid black line shows the estimated responsewhile the dotted black line depicts the 95 percent confidence intervals.

Panel-data Evidence
We next turn our attention to panel data evidence on the potential relationship between growth and financial conditions in Emerging market economies. Specifically, we execute the Dumitrescu and Hurlin (2012) panel granger causality tests tailored for heterogeneous panel data. This procedure hinges on computing individual Wald statistics of Granger non-causality for each cross-sectional unit which are then averaged across the full sample.[33] The results, reported in the table below, strongly support Granger causality from EMFCI to EMGDP at the one percent level of significance. Conversely, we observe no evidence of causality from EMGDP to EMFCI. Furthermore, the tests validate the robust, bi-directional feedback between the global financial cycle and EMFCI.

Figure C3. Panel Granger Causality Test

Y↓	X→	EMFCI	GFC	GDP
EMFCI	**z-value**		8.882	-0.832
	p-value		0.000***	0.406
GFC	**z-value**	13.402		-0.596
	p-value	0.000***		0.552
EMGDP	**z-value**	25.064	20.355	
	p-value	0.000***	0.000***	

Note: The above table shows the results from the panel granger causality tests proposed by Dumitrescu and Hurlin (2012). Row variables cause column variables. ***: p < 0.01; **: p < 0.05; *: p < 0.1.

To further explore the dynamic relationship between financial conditions and GDP growth in emerging market economies, we estimate a panel-VAR model using GDP and financial conditions at the country-level.

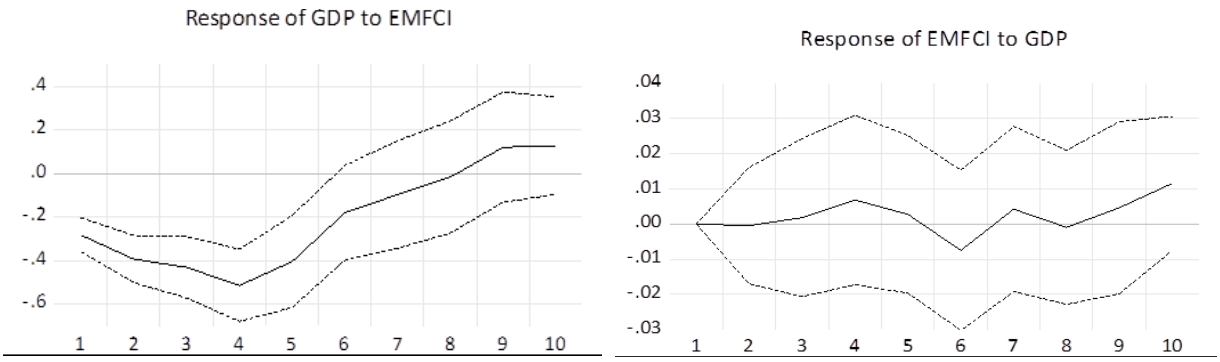
[33] Beyond its computational parsimony and accommodation of cross-country heterogeneity, this test demonstrates several merits. It preserves test power even when confronted with limited values of *N* and T, and seamlessly applies to unbalanced panel configuration/.

More specifically, we apply a panel VAR-X model i.e., a panel vector autoregression model with an additional exogenous (X) covariate. Panel VAR-X models are popular for analyzing the effect of global shocks in the case of small open economies, especially emerging market economies. In a panel VAR-X model, a stationary k-dimensional vector Z_{it} is modelled in terms of its own past values and the past values of an m-dimensional vector x_t of exogeneous covariates:

$$Z_{it} = d_i + \sum_{k=1}^{q} \gamma_k Z_{it-k} + \sum_{j=1}^{s} B_j x_{t-j} + u_{jt} \quad \text{(C1)}$$

The panel VAR-X model is estimated with country-fixed effects on the 18-country sample. We use a Cholesky scheme to identify the model. The impulse responses from the panel VAR-X setup are denoted below in Figure C4. The left panel shows the response of EMGDP to a tightening in EMFCI. A tightening in financial conditions leads to a decline in GDP growth for at least four quarters and continues to remain negative for at least six quarters before it reverts to zero. The negative response of EMGDP to an EMFCI shock is broadly consistent with the results from our model. The right panel shows the response of EMFCI to a positive shock to EMGDP. The on-impact response of financial conditions to a GDP shock is seen to be zero i.e., on the first quarter itself, which is on account of the Cholesky ordering scheme with GDP ordered after FCI in the variables ordering. Like the VAR model, the response of the FCI to a GDP shock continues to remain statistically insignificant.

Figure C4. GDP Growth and Financial Conditions in a Panel VAR model - Impulse Responses Analysis



Source: Authors' calculations.

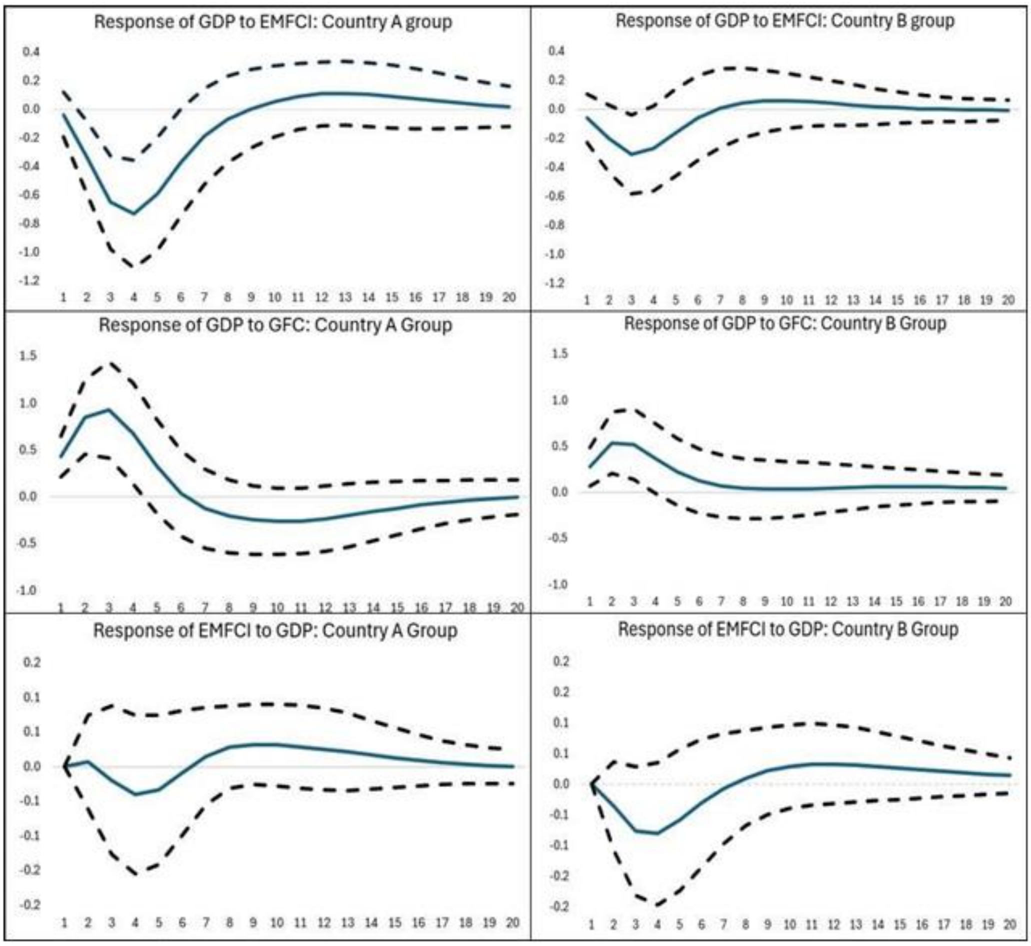
Note: The above figure plots the impulse responses obtained from a panel VAR model with country- fixed linkages containing FCI and GDP as endogenous variable. Global financial cycle (GFC) index was taken as an exogenous covariate in the panel VAR model. The left panel shows the response of GDP growth to a one standard deviation (sd) shock to FCI while the right panel shows the response of FCIto GDP shock. The solid black line shows the estimated response while the dotted black line depict the 95 percent confidence intervals.

We also test various alternate specifications of the VAR and panel VAR model described above. We do not present all the results for brevity. However, the results remain qualitatively the same for all such specifications.

Group-wise Results

The VAR-based group-wise impulse responses are shown in Figure C5 below. For Group A countries (where the twin-deficits condition is present), a tightening of the EMFCI leads to a more pronounced dampening of growth prospects compared to Group B countries, as indicated by the higher B_{fg} coefficient estimate for Group A. This growth slowdown exerts additional pressure on twin-deficits economies, creating a crowding out effect that keeps growth subdued for a longer period for Group A countries than for Group B countries. Notably, Group A exhibits a significant and positive B_{gf} coefficient estimate, unlike Group B. Together, these factors contribute to a stronger and more prolonged GDP responses to EMFCI tightening, consistent with the impulse responses observed for both groups.

Figure C5. Group-wise Macro-financial Dynamics - Impulse Responses for Group A and Group B countries



Source: Authors' calculations.

Note: The above figure plots the impulse responses obtained from a panel VAR model with country- fixed linkages containing FCI and GDP as endogenous variable. Global financial cycle (GFC) index was taken as an exogenous covariate in the panel VAR model. The left panel shows the response of GDP growth to a one standard deviation (sd) shock to FCI while the right panel shows the response of FCIto GDP shock. The solid black line shows the estimated response while the dotted black line depict the 95 percent confidence intervals.

Model Simulation Exercise

D.1. Simulations Based on Alternate Interaction Matrix Structures

Table D1. Model Simulation: Summary Results

B_{ij} **Matrix**	Description	**AICc**	**Log-L**	**Interaction**	**Covariate**
$\begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix}$	Unconstrained	242.5	-108.2	2000-2019	2000-2019
$\begin{bmatrix} B_{11} & 0 \\ 0 & B_{22} \end{bmatrix}$	Diagonal and Unequal	282.2	-130.4	2000-2019	2000-2019
$\begin{bmatrix} B & 0 \\ 0 & B \end{bmatrix}$	Diagonal and Equal	280.4	-130.6	2000-2019	2000-2019
$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$	Identity	305.9	-144.5	2000-2019	2000-2019

Source: Authors' calculations.

Note: The above table shows the model diagnostics for various structures of the interaction matrix of the MARSS model described in equation (5)-(7). The model is estimated at the aggregate EM-level using median values of the all variables.

Simulations Based on Different Input Variables

$$\begin{pmatrix} \mathbf{EMFCI} \\ \mathbf{GFC} \end{pmatrix}_{\mathbf{t}} = \begin{pmatrix} \mathbf{B_{11}} & \mathbf{B_{12}} \\ \mathbf{B_{21}} & \mathbf{B_{22}} \end{pmatrix} \begin{pmatrix} \mathbf{EMFCI} \\ \mathbf{GFC} \end{pmatrix}_{\mathbf{t-1}} + \begin{pmatrix} \mathbf{C_{11}} \\ \mathbf{C_{21}} \end{pmatrix} (\mathbf{GDP})_{\mathbf{t}} + \begin{pmatrix} \mathbf{w_{fci}} \\ \mathbf{w_{gfc}} \end{pmatrix}_{\mathbf{t}} \qquad \text{(D1)}$$

$$\begin{pmatrix} \mathrm{GFC} \\ \mathrm{GDP} \end{pmatrix}_{\mathrm{t}} = \begin{pmatrix} \mathrm{B_{11}} & \mathrm{B_{12}} \\ \mathrm{B_{21}} & \mathrm{B_{22}} \end{pmatrix} \begin{pmatrix} \mathrm{GFC} \\ \mathrm{GDP} \end{pmatrix}_{\mathrm{t-1}} + \begin{pmatrix} \mathrm{C_{11}} \\ \mathrm{C_{21}} \end{pmatrix} (\mathrm{EMFCI})_{\mathrm{t}} + \begin{pmatrix} \mathrm{w_{fci}} \\ \mathrm{w_{gfc}} \end{pmatrix}_{\mathrm{t}} \qquad \text{(D2)}$$

Table D2 Model Simulation: Summary Results

Model Coefficients	
B_{11}	0.82***
	(0.12)
B_{21}	-0.15**
	(0.09)
B_{12}	0.32**
	(0.09)
B_{22}	0.77***
	(0.07)
C_{11}	-0.18
	(0.13)
C_{21}	0.06
	(0.09)
AICc	252.38
Log-likelihood	-113.13
Interaction Period	2000-2019
Covariate Period	2000-2019

Source: Authors' calculations.

Note: The above table shows the maximum likelihood estimates for model specifications with different input variable configurations, corresponding to the model outlined in (D1). The model is estimated at the aggregate emerging market economies-level. Estimated standard errors are shown in parentheses. Confidence intervals (CI) at 5 percent level of significance and other diagnostics are provided alongside.

PUBLICATIONS

Emerging Market Cycles: Twin-Balance Sheet Conditions and Macro-Financial Linkages
Working Paper No. WP/2025/216