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COVID-19
Response and Recovery
Mobilizing financial resources for development

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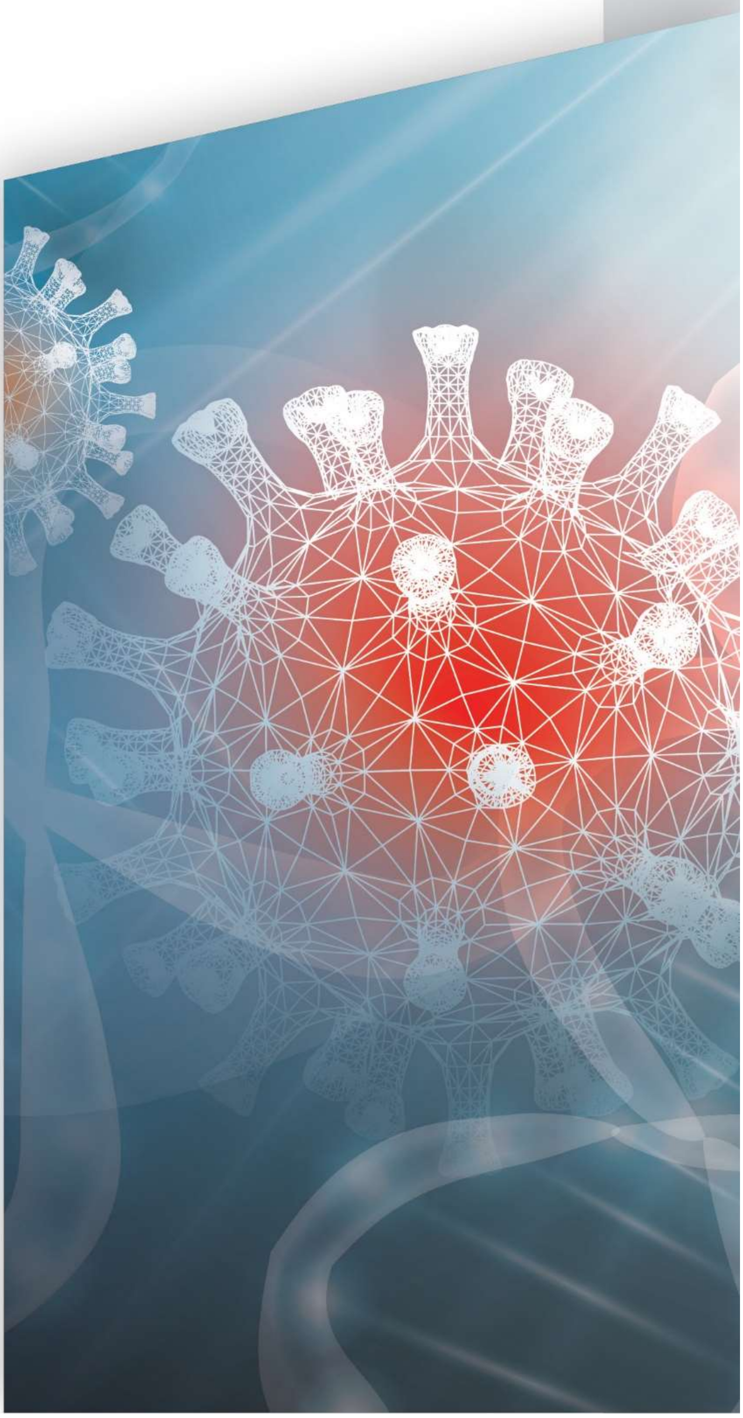

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Between stress and strain: understanding, measuring, and analysing financial conditions in developing countries in times of Covid-19 and beyond

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Rachid Bouhia, Economic Affairs Officer, UNCTAD

Guillaume Blanc, Justine Falciola,

Patrick Kaczmarczyk and Julien Bodelet, Consultants, UNCTAD

About the COVID-19 Response and Recovery project

This paper is an output from the project “Response and Recovery: Mobilising financial resources for development in the time of COVID-19”, which is co-ordinated by the Debt and Development Finance Branch of UNCTAD and jointly implemented with ECA, ECLAC and ESCAP. This project is one of the five UN Development Account short-term projects launched in May 2020 in response to the COVID-19 crisis.

The project aims to enable low-income and middle-income developing countries (LICs and MICs) from Africa, Asia-Pacific, and Latin America and the Caribbean to diagnose their macro-financial, fiscal, external financial and debt fragilities in the global context, and design appropriate and innovative policy responses to the COVID-19 pandemic leading toward recoveries aligned with the achievement of the Sustainable Development Goals (SDGs).

Abstract

This paper presents a novel conceptual and methodological approach to measuring financial conditions in developing countries drawing on dynamic factor analysis. Our theoretical foundation to construct and interpret the model is based on a Minskian framework of financial instability. Conceptually, instead of analysing financial conditions for individual economies, we cluster various countries with similar financial dynamics into different groups. This has the advantage of alleviating data scarcity and data quality problems. Our methodology also allows for potential regime changes in countries through various specifications for loadings. The paper presents the results of our approach with fixed loadings, which resulted in five different clusters. Most countries fall into a classic boom and bust type of financial cyclicality that renders stable and long-term development financing inherently difficult. We finish the paper by outlining our policy recommendations on the global level as well as targeted measures for each cluster.

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Section I – Introduction

The COVID-19 crisis has exacerbated the many challenges that confront developing and emerging economies. Especially in the face of the expected unwinding of emergency policy measures and the tightening of monetary conditions to curb inflation in the North since the last quarter of 2021, the global South is bracing itself for new turbulences in international capital markets. Ever since the liberalisation of global finance, financial conditions in developing regions have been vulnerable to shocks and changes in market sentiments.

All hopes for profound reforms in the international financial system to put it back at the service of economic development after the 2008 global financial crisis (GFC) were dashed. Despite the introduction of new national and international supervisory bodies, as well as the implementation of timid measures in the banking sector, most financial risks and channels of transmission to the real economy were not addressed. The biggest banks have become even bigger, the business of toxic financial assets has grown, while shadow banking has carried on its expansion. Thus, in early 2020, the Covid-19 pandemic hit the world economy after a decade of increasing financial vulnerabilities in developing countries and heightened sensitivity to external factors, such as global monetary conditions and commodity prices. More recently, the outbreak of the war in the Ukraine put additional pressure on these vulnerabilities and added further uncertainty and insecurity to the global political and economic stability

Globally, countries are finding the efficacy and execution of monetary policy is inherently more difficult in this challenging environment. More than ever, steering monetary policy requires looking beyond conventional macroeconomic indicators, such as inflation or output gaps. Central bankers must take a more comprehensive approach, which notably considers spillover effects via the external account, triggered by capital flows and investors' reactions in global financial markets. However, quantitative indicators to do so are scarce, especially in the case of developing countries.

Against this background, there have been several initiatives lately to develop financial conditions indicators (FCIs), aiming to shed light on the health of the financial sector and its responsiveness to shocks. The main purpose is to pre-empt financial crises and their escalation into currency and/fiscal, and ultimately, economic crises. Our research follows this track. Our contribution is thereby threefold. First, in line with previous work by UNCTAD on the issue of financial conditions, we add a theoretical framework, rooted in Keynesian and Minskian economic theory, that underpins the interpretation of financial stress and instability. Such frameworks were, at best, incomplete in the existing literature on FCIs, which mostly focuses on econometric and statistical aspects, without paying much attention to the interpretation of the output and evolving narratives. In particular, we found that much of the FCI literature is based on econometric tools initially developed for "business cycle theories" without closely examining the adequacy of their application to the financial sector. Especially in the context of global financial liberalisation, this has important implications not only in terms of the interpretation of FCIs, but also regarding the assessment of their performance.

Second, most FCIs currently cover advanced economies and, to a much lesser extent, some emerging economies. In the literature, most developing economies (low- and middle-income countries) have been left aside, probably due to scarcity and poor quality of financial data. In this research, we set out to collect data for these countries, and we put in place several methodological innovations to better accommodate their idiosyncrasies. We posit that a single, global indicator of financial conditions is insufficient to capture the complexity of interdependent economies. On the other hand, the volatility and scarcity of the data for some of the countries makes it difficult to compute meaningful FCIs at the country level: for some countries, these FCIs are either too volatile or may suffer from infrequent updating. We strike a balance between these two options by grouping the countries in clusters based on the similarities of their economies and computing the FCI that is representative of the members of the clusters. More specifically, we adopted a two-stage approach: in the first stage, we computed country-level FCIs for 76 developing and emerging economies[1] through factor analysis. Subsequently, we classified all these economies into different clusters by using either ex-ante classifications or an ex-post approach, i.e., by grouping countries with similar patterns of financial conditions together, as defined by the data. The FCIs are then calculated for each cluster. This approach entails several advantages. The findings are more robust, given that data gaps and low data quality have a lower distortive impact. Moreover, especially for the most vulnerable and poorest economies in the world, which suffer from significant data gaps, the aggregated FCI allows to derive economic conclusions and policy recommendations by capturing the evolution of similar economies with more available data. We stress that the aggregated FCI is not meant as a substitute, or indeed a predictor, for the country-level FCI of those countries with sufficient data.

[1] The list of countries is based on UNCTAD country classifications as of September 2020: https://unctadstat.unctad.org/EN/Classifications.html

Our third main contribution is to propose taking into consideration potential regime changes in countries (such as a sudden opening to international capital flows) by allowing structural breaks in the country FCIs through conditional time-varying factor analysis or nonparametric time-varying factor analysis. As a result, our methodology allows for three specifications regarding the country FCIs (static factor analysis, conditional time-varying factor analysis and nonparametric time-varying factor analysis) and two specifications regarding the cluster FCI (ex-ante grouping versus ex-post clustering). This large variety of building options offers greater flexibility to tailor the FCIs to the users' needs.

The paper is structured as follows. Section II discusses the notions of financial conditions and financial stress in the literature and presents our conceptual framework based on Minskian theory. Section III introduces the financial data that we collected, highlights the data challenges in low- and middle-income countries, and makes the case for a cluster approach. Section IV starts with a technical literature review on the use of factor analysis and dynamic factor models. It then presents our methodology based on the two-stage approach described above, including a comparison with alternative methods and a proposition of some possible extensions. Section V presents our findings, discusses the different specifications, and proceeds with an economic analysis of the results related to the ex-post clustering. Section VI derives some global and cluster-targeted policy recommendations and concludes.

Section II – Conceptual framework

Developing indicators to monitor financial stress is a challenging task. Although some research on this topic was conducted prior to the GFC, it was especially after the turmoil of 2008, which brought the world economy down to its knees, that many economists have recognised the need to develop multidimensional tools that could function as early warning systems. The logic behind this is simple: if malfunctioning of financial markets were to be detected early, policymakers could be able to take preventive and corrective measures that could contain the adverse effects that financial crises have on the real economy (Kliesen et al., 2012). Although the very concept of FCIs takes a distance to the notion of self-equilibrating financial markets, what is often missing is a comprehensive theoretical framework that would facilitate the interpretation of FCIs and provide a solid grounding for deriving policy conclusions. Moreover, since most FCIs focus exclusively on periods of financial stress, this overlooks that the seed of the downturn is planted, following Minskian theory, during the boom periods. The turbulent experiences over the past 50 years require therefore an understanding that accounts for the *inherent* instability of financial markets, including their recurring tendencies of false pricing in both directions, i.e., continuous under- and overshooting. This, in turn, necessitates a radical departure from neoclassical approaches to conceptualise capital markets, which argues that any frictions or episodes of stress are a mere temporary malfunctioning of otherwise stable markets.

In this section, we provide a brief overview of the conceptualisation of financial stress. Then, we develop an alternative Minskian framework that captures fundamental uncertainty and, concomitantly, the inherently unstable nature of financial markets.

Financial stress and financial crises

Any statistical concept and analysis require for the interpretation of the coefficients a coherent theoretical framework. As per the concept of financial stress, economists and statisticians were and continue to be faced with a two-fold challenge. On the one hand, there is the task of operationalising a concept that cannot be tangibly measured. On the other hand, a comprehensive narrative about the output coefficients cannot be provided without a theoretical understanding of the underlying drivers.

Regarding the former, the literature usually relies on composite indices that measure latent conditions, such as developments in equity, bond, or foreign exchange (FX) markets, or variables that indicate the resilience and soundness of the banking sector (Cardarelli et al., 2011; Chadwick & Ozturk, 2019). For FCIs for emerging economies, variables related to external debt and sovereign risks are additionally considered (Cevik et al., 2013). The underlying idea is that such observable indicators are linked to at least one of the key features that economists associate with financial stress. These features include, following Hakkio and Keeton (2009), an i) increased uncertainty about the fundamental value of assets and ii) about the behaviour of other investors, iii) increased asymmetry of information, as well as iv) decreased willingness to hold risky and/or v) illiquid assets. Whatever the trigger and nature of heightened stress levels might be, once a certain threshold is crossed, financial market participants tend to rush into liquidity, notably cash, which reduces consumption, demand, and investments, leading to a sharp contraction of economic activity (Keynes, 1936). Thereby, the scale of the downturn can be amplified by 'animal spirits' and herd behaviour if panic spreads through the markets, investors start to liquidate their positions, and asset values evaporate (Minsky, 1986, 1992).

Emerging and developing economies are particularly vulnerable to the vagaries of international finance. On the one hand, they recurringly face the problem of "sudden stops", i.e., the reversal of short-term hot money flows and a concomitant collapse of asset prices and their exchange rates (Dornbusch et al., 1995). Such capital flight can be triggered by financial crises originating in developed countries, the tightening of monetary policy in northern currency areas – notably in the US – or shifts in market sentiments given the building-up of unsustainable imbalances, e.g., in the current account. As the stabilisation of prices in FX, securities, or interbank markets (for pegged or dollarised currency regimes) requires access to foreign reserves, emerging and developing countries often do not have the sufficient resources to intervene.

On the other hand, it is not only the sharp reversals of capital flows – "the stops" – which pose a problem, but also "the starts". The inflow of capital from developed countries into the modest domestic capital markets of emerging and developing economies often contains the seed of future crises – especially if volatile and speculative portfolio flows account for the majority of capital inflows. Haldane (2011) conceptualised this as the "Big Fish Small Pond Problem" – the big fish being large capital inflows from the global north and the small pond constituting the comparatively small capital markets in the south. As Haldane (2011) notes, when a big fish enters a small pond, this causes "ripples right across the international monetary system" (p. 2). In the case of developing and emerging economies, these ripples manifest in persistent false pricing, especially in form of appreciating exchange rates, which worsen the capital-importing economies' competitiveness and current account position, and therefore erode the productive base of the economy (UNCTAD, 2009, 2011a). The building up of macro-economic imbalances sets the stage for future crises, as it often precedes the emergence of financial stress (UNCTAD, 2011b). Our proposed FCIs explicitly considers this destabilising nature of capital inflows, too.

The turbulent experiences of the world economy, and in particular developing and emerging countries during the period of hyperglobalisation, suggest that an understanding of financial stress and crises must go beyond a superficial analysis of capital market indicators. A coherent conceptualisation and embeddedness of FCIs, especially with regards to policy conclusions, requires a deep theoretical understanding of the very nature of capital markets.

A Minskian approach to understand financial markets

Especially since the GFC, Minsky's work on financial markets has witnessed a renaissance in the mainstream economics for its explanatory power of the near-death experience of capitalism. Prior to the drama of 2007-2008, economists and policymakers, in the firm belief of the workings of the "invisible hand", celebrated the deregulation of financial markets and liberalisation-induced end of the business cycle and the "Great Moderation" (Bernanke)[2]. Neoclassical economic theory nourished their optimism, as the conceptualisation of capital and capital flows does, by definition, not allow for inherent market malfunctioning. Neoclassical economists understand capital as an all-purpose good: it is – at the same time – a consumer good, the only investment good, it constitutes savings, the means of funding, capital employed in production and so on. Therefore, in a neoclassical world, economists pick and choose whatever they want capital to be for the purpose at hand. Consequentially, there is no cognitive dissonance in the economics profession when conceptualising capital flows as being either identical to goods flows or, alternatively, tied to 'real' economic conditions, i.e., the marginal productivity of and returns on capital. This has led to a hopeless confusion among economists as well as an inability to explain the ups and downs on global financial markets. We provide a more coherent outline of neoclassical theory and the 'capital issue' in the appendix (Annex II).

Minsky takes radical uncertainty as his point of departure. Although he wrote much of his work in the 1960s and 1970s, mostly on equity markets of the US economy, his theoretical insights have been widely since applied to other financial markets as well, including for the analysis of developing countries (Gallagher & Kozul-Wright, 2019; Kregel, 2000) Put differently, although

[2] See Bernanke's speech at the 2004 meetings of the Eastern Economic Association: https://www.federalreserve.gov/boarddocs/speeches/2004/20040220/

his model “was originally developed to explain credit and economic cycles in industrialized market economies with highly-developed financial institutions and markets”, it “[provides] a sound interpretation tool for understanding (…) financial and economic booms and crises” – including “the series of financial crises in developing and newly industrializing countries” ((UNCTAD, 2007), p. 20). Minsky explains why financial markets are inherently unstable and prone to over- and under-shooting equilibrium prices, which has devastating consequences especially for the developing world due to their financing constraints (UNCTAD, 2019). For this reason, Minsky’s work has regularly served as the theoretical foundation for UNCTAD’s analysis of financial markets, as well as deriving of policy recommendations (cf., in particular, UNCTAD’s Trade and Development Reports 2017-2020).

In this paper, we employ Minskian theory to frame an understanding the very issue we intend to measure – i.e., financial instability – and interpreting the data. It is *not* intended to provide details on the technical input of the indicator as such, but rather a conceptual overarching framework for financial instability and, most importantly, on the interpretation of the results and clusters.

Ontologically, Minskian theory is firmly rooted in the Keynesian idea of fundamental uncertainty. Since the future is unknown to us, the necessity to act under such conditions implies that the best we can do is to rely on conventions as guidance for our decision-making. In a reference to Keynes (1937), Minsky (2008) outlines that decisions are predominantly based on the assumption that “the present is a ‘serviceable guide to the future,’ (…) that existing market conditions are good guides to future markets, and [that] ‘we endeavour to conform with the behaviour of the majority or the average’” (p. 64). Hence, our decision-making is a function of the interpretation of current market conditions, based on the past, as well as our interpretation of how others perceive the world. As the views of the future, however, are “subject to sudden and violent changes”, it means that all these techniques we employ to feed our decision-making, regardless of how sophisticated they might appear, “are liable to collapse” (Keynes, 1937, p. 214-215). This tendency can be amplified by high leverage, herd behaviour, as well as increasingly complex financial, political, and social interrelations (UNCTAD, 2007, 2015) . Thus, the *key* insight of Keynesian economics suggests that it is uncertainty itself that renders the views of market participants and therefore their decision-making and behaviour inherently unstable and unpredictable.

While instability is fundamentally linked to uncertainty, through his conceptualisation of the economy as a set of interrelated balance sheets, Minsky introduced a further innovation of how to understand the dynamics on capital markets. Thereby, it is first important to recognise that each actor in a monetary economy has a financial portfolio, which consists of assets owned and liabilities owed. This financial portfolio, which is unique to each actor, constitutes a sequence of both incoming and outgoing cash flows. Liabilities come with future cash flow commitments *to* other parties. Financial assets, on the other hand, are a claim on future cash flows *from* other parties (or, in the case of cash, an insurance against potential market vagaries).

The character of these cash flows depends on the nature of the asset or liability. Debt issued by firms, for example, is inevitably conditional, as it depends on judgement bounded by inability to know the future in an open complex and therefore uncertain system. Government debt, by contrast, if issued in a national currency, will be honoured beyond the shadow of a doubt, as the government cannot run out of its own cash. Cash itself, in turn, plays a specific role in the monetary system. It does not yield any interest, but at the same time, it can settle any financial liability and meet the cash flow commitments that the latter entails. Cash comes therefore with a downside, in form of foregone earnings, and an upside, in form of liquidity preference as well as an insurance against a shortfall of cash-receipts. Since Minsky's theory draws upon Schumpeterian theory of credit and finance, it should be noted that, contrary to the neoclassical conception of the capital market with its limited stock of savings that are passed on as loans, he acknowledges the *ex-nihilo* character of money and credit (Minsky, 1992). Minsky "takes banking seriously" (ibid., p. 6) by firstly considering that money is created by the banking sector through credit, for which no prior savings are required. Secondly, banking – defined in a wider sense to encompass all actors on financial markets – constitutes "a profit-seeking activity", which means that, as in any other capitalist industry, bankers will "strive to innovate in the assets they acquire and the liabilities they market" to increase their profitability (ibid.). Adding uncertainty into the mix now allows us to understand as to why financial markets are inherently unstable. As Minsky writes, uncertainty means that the ratio of cash receipts to cash commitments is always subject to speculation, as financial assets and liabilities "embody yesterday's views and both earn and commit today's and tomorrow's receipts." (Minsky, 2008, p. 75). In other words, regardless of whether financial market participants are bullish or bearish, "to decide is to place a bet" (ibid.).

Booms and busts

Through financial interactions between economic units and changes in sentiments on financial markets, the liability structure of the economy is always changing. This allows us to understand what lies at the heart of financial speculation (far beyond equity markets) and why developing and emerging economies were often subject to volatile boom and bust cycles. In boom periods, speculative bets usually pay off. Capital assets increase in value and cash receipts from assets suffice to pay cash commitments and often even outstrip previous expectations. This increases confidence in the market to predict the future and encourages more debt financing, as the higher capital valuations lower the ratio of cash commitments to valuations, which offers additional room for leverage within the old liability structure. Moreover, better financial performance through higher earnings per share and tax deductibility of loan interest further push firms into debt. Finally, in today's financial system, in which credit creation has increasingly moved away from classical bank lending towards securitised market-based financing, there is the additional effect that higher prices of the securities, which serve as collateral for repo deposits, allow financial actors to further leverage their positions (Gabor, 2020a). Thus, as Minsky foresaw, from a technical point of view, the innovations in market-based finance have greatly increased the scope for leverage and rendered oversight of how sustainable the emerging liability structure may be, increasingly obscure, as recurring turbulences on repo markets indicate (Sissoko, 2020), from which developing and emerging markets are affected.

Therefore, good times and financial innovation change risk perceptions on financial markets, leading to increasing debt to equity ratios. As long as the ever more optimistic expectations regarding yields and cash receipts are met, capital gains accrue to investors, liquidity in financial markets remains high, and the virtuous cycle keeps rolling. The turning point arrives when market sentiments change. As a boom evolves, and confidence over time decreases, and borrowing from other financial institutions slows down. Investors suddenly deem their liability structure too daring, so that they start a conservative restructuring of their balance sheet. When cash commitments outstrip (desired) cash receipts, due to, for example an excessive share of external financing or some unforeseen shock or default, investors try to improve their position by first reducing their own leveraged positions. This involves either a sell-out of financial assets or a mere slowdown of acquisitions at first, which can later accelerate. When many investors try to raise cash at the same time, asset prices fall, and liquidity dries up. A self-reinforcing cycle sets in as margin calls and panic in the market further push down the value of financial assets and drive up the demand for cash. Meanwhile speculators, having gone long during the boom period in expectation of price increases, now bet on a bear market by going short and thereby exacerbate the downturn. In the real economy, non-financial firms equally start to use their internal funds to clean up their balance sheets, instead of investing in their productive capacities. This affects the overall investment dynamic and aggregate demand, so that a downturn on financial markets is followed by recessions in the economy. Minsky outlines that the only way to halt the debt-deflationary meltdown is through decisive government intervention. Only the government, by means of its central bank, can stabilise cash flows and therefore asset prices.

During a depression or recession, the sentiments on financial markets remain depressed. As, in a world of uncertainty, the present continues to serve as a guide for the future, the outlook for businesses remains grim and investors act accordingly. Paying down liabilities and cleaning up the balance sheet constitute the primary objectives in the market, leading to a balance-sheet recession. As government policy eventually stabilises the market and the recovery sets in, the memories of the past erode, and the cyclical process starts anew. After a period of prudent hedge financing, the capital gains and the asset revaluation indicate to businesses that there is room for leverage. Positive feedback loops confirm investors' bullish outlooks, shift risk perceptions, and increase debt-to-equity ratios, which leads to the increasingly fragile liability structure of speculative finance until market sentiments reverse and deleveraging sets in. Hence, "stability breeds daring" and therefore becomes destabilising (Minsky, 2008, p. 125).

Implications for FCIs and capital markets in developing countries

Minsky thus puts forward a theory "fully rooted in 'the City' and 'Wall Street'" (Minsky, 2008 p. 127) that explains booms and bust cycles in a way that is not confined to US equity markets in the 1960s and 1970s, but also to developing and emerging market economies alike (Gallagher & Kozul-Wright, 2019). Moreover, as Minsky regards financial instability as a systemic issue, this shifts the focus away from merely analysing domestic variables as the outcome of crisis towards an analysis of the financial system, and thereby notably speculative financial activities – which is particularly relevant in a hyper-globalised world (ibid). This implies, on the one hand, an analysis of capital flows between the centre and periphery of the global economy, and, on the other, of the institutional capacity of developing and emerging economies to intervene and stabilise markets. On both fronts, developing and emerging economies are victims of an international financial and economic order that works for the benefit of the few, not the many.

Widespread capital account liberalisations in the global south together with financial innovation have rendered in local capital markets increasingly complex and fragile (Bouhia & Munevar, 2019; Gabor, 2020b). Through speculation in various financial asset classes – including real estate, currencies, commodities, equities, derivatives, and other securities –

developing and emerging economies are now more than ever exposed to the vagaries of international finance. Whilst the speculative Minskian dynamics that play out in the financial markets of developing and emerging economies are detached from economic fundamentals, they do have a significant impact on development trajectories. When short-term speculative capital flows enter financial markets of developing and emerging economies, this adversely affects the local economy in different ways. The most prominent channel is a direct hit to competitiveness, as the bets of carry traders, who exploit interest rate differentials between currency areas, lead to an appreciation of the real exchange rate and, concomitantly, current account deficits and an erosion of productive structures (UNCTAD, 2007). In other cases, speculation with commodity derivatives increases the prices of food and energy resources. While some countries might benefit in the short run from, for example, higher oil prices, others suffer. Especially as food and energy make up a large part of the consumption basket for many developing countries, such speculative frenzies fuel inflation, hunger, and poverty, and induce the central bank to raise interest rates (which, in turn, further suffocates the economy). On the other hand, those countries who benefit in the short run from higher commodity prices often neglect the required political economic action to advance their structural transformation. Higher commodity prices function as a positive productivity shock that offsets the pressure to diversify the economy, and, as soon as market sentiments change, it leaves the economy in peril.

For a sustainable development agenda, stable financing and capital market conditions are *sine qua non*. Yet, instead, as Minskian theory suggests and our analysis below indicates, financial conditions in developing and emerging economies resemble roller coaster ride. The general patterns are always the same: short-term oriented speculators project the near-term future based on present market sentiments. Rising prices across financial asset classes confirm previously held views, increase confidence, and lead to further bets on a bullish market. As long as capital gains and incoming cash receipts remain in line or exceed investors' estimates, prices continue to rise and encourage greater leverage, which, in turn, increases financial instability, as small changes in market expectations now have a disproportionate effect on capital flows. Such changes in market sentiments can arise either from doubts about the sustainability of cash receipts and capital gains of financial assets – for example due to the build-up of unsustainable imbalances in the external sector – or from an increase in cash commitments through higher interest rates in the borrowing currency. The reverse capital flows can leave the exchange rate and foreign revenues in freefall, freeze credit markets, increase borrowing costs, and lead to imported inflation, as investors flee into safe assets and project the present state of depression indefinitely into the future (Bouhia & Munevar, 2019). As opposed to developed economies, which, backed by their central banks, can rely on the state to stabilise cash flows and asset prices, developing and emerging economies often cannot resort to such stabilising measures due to external constraints and a limited stock of foreign reserves. They are left to the vagaries of international finance, as the continuous booms and busts greatly impede the development of their productive economy.

When measuring financial conditions via a single indicator, the endogenous nature of financial instability implies that the indicator has to essentially capture the changes of latent market sentiments, which could subsequently feed into a self-reinforcing downward dynamic or fuel an unsustainable boom, as theoretically outlined above. Minsky's main political conclusion, which we will draw on in our policy recommendations below, is that the only way to keep the instabilities somewhat in check is to set up a financing regime in which very simple rules constrain the potential for leverage and innovation in the system. As long as finance is held in check, the cyclical effects can be largely, if not entirely, contained (Minsky, 1986). In periods where this was not the case, financial crises regularly occur in various forms.

Section III – Data: overview and challenges

In this section, we present the data collected for our proposed FCIs. The selection of variables is based on the literature on FCIs as well as our conceptual framework previously discussed. Subsequently, we highlight the issues and challenges which particularly affect low- and middle-income countries and justify a clustering approach. Last, we set out in a detailed way how the data was processed to comply with the specifications of a factor analysis.

Overview of the variables

The literature on FCI tends to measure underlying financial stress by changes in observable financial variables, which are assumed to indicate arising stress in capital markets. Such variables include a range of monetary, financial and macroeconomic indicators, such as interest rates, exchange rates, GDP, capital flows, various market indices (stock market, real estate…) and so on. The macroeconomic and financial variables that we selected for our analysis are provided in Table 1 below. The data consist of monthly and quarterly observations which span from January 2005 to March 2021. The dataset is compiled by combining various data series from Eikon Datastream[3]. For some countries, capital flows were calculated, if missing, using accounting equations applying in the Balance of Payment. Government bond yields were introduced as spreads We only included country-specific variables.

[3] Formerly known as "Thomson Reuters Datastream"

	Variables	Description
1	CPIYOY	Percentage of CPI annual change for same month
2	CREDIT	Amount of certain category of credit (to different sectors)
3	CREDIT2	Credit owned by non-residents
4	DEBSER	Debt service ratio index for the private and non-financial sector
5	DEPRAT	Deposit rate
6	DISCRA	Discount Rate
7	ELMIP	ELMI Plus index[4]
8	EMBI	Emerging Markets Bond Index
9	EMBIBS	EMBI[5] Blended Spread
10	EMBISO	Merill Lynch Emerging Markets Sovereign Bond Index
11	ESTATI	Real estate index
12	FINANI	Financial sector index
13	FUNDUS	Use of Fund Credit
14	GDP	GDP quarterly
15	GOVYLD	Government Benchmark Bid Yield 10 Years
16	INOVER	Interbank and overnight rate, percent
17	LENRAT	Lending Rate
18	MONAGG	Monetary aggregate M3
19	MONYOY	Percent. of money and quasi-money change between the month of one year and the month of next year
20	NOPERL	Percentage of non-performing loans to total gross loans
21	PASECI	Index of a key domestic sector [6]
22	PortDer_Assets	Portfolio investment outflows
23	PortDer_Liabilities	Portfolio investment inflows
24	PRICOM	Price of commodity
25	PRIMRA	Prime rate, percent
26	REER	Real Effective Exchange Rate index
27	RESERV	Official Foreign Reserves
28	RESMOM	Percentage of official reserves change between two following months

[4] JPMorgan Emerging Local Markets Index Plus
[5] Emerging Markets Bond Index
[6] E.g., the main commodity sector for commodity-exporters

29	RESPRO	Residential property prices index
30	RESYOY	Percentage of official foreign reserves change between the month of one year and the same month of the next year
31	STOEXI	Stock exchange index
32	TREBIL	Treasury Bill short term between 3 months and 1 year
33	VOLATI	Volatility index

Table 1 Description of country variables

Scarcity and poor data quality

To date, the literature on financial stress has almost exclusively focused on advanced economies to measure country-level financial conditions. Amongst other factors, one decisive factor explaining this tendency is certainly the scarcity and/or poor quality of financial data for developing countries. In this section, we further document this issue by considering our dataset of financial variables covering 81 developing countries[7]. We show that the severe lack of data impedes us from building country-level FCIs for these developing countries and therefore suggest a methodological innovation: as previously mentioned, in order to better accommodate low or middle-income countries specificities, we propose a clustering – or regrouping – of countries with similar financial conditions to bypass the constraints relating to financial data scarcity. By grouping countries together based on the similarities of their historical data, the gaps in the data of one country can be filled-in by the information provided by the other member of its group.

A first glance on the data exposes the severity of the data scarcity issue. Indeed, in our original sample, there is no time series which has complete information for all time periods and across all countries. Table 5, provided in Annex II, shows the descriptive statistics of our original sample as well as the percentage of missingness of countries classified per income level. We see that, although the sample is roughly equally spread across LICs (N=5293),

[7] 4 countries will be excluded from our final computation for the FCIs due to very serious issues in their input data (cf. subsection on “Data processing”).

MICs (N=6030), and HICs (N=5025) some series are almost fully missing (e.g.. CREDIT2), while others have few missing observations (e.g. PRICOM).

The histogram in Figure 1 shows the distribution of the number of missing series across all countries in our sample. On the x-axis, we have the number of series that are missing. The height of each bar, as well as the number in white, show how many countries fall in the given category. In fact, we see that all countries have missing series. Seven countries have between 4 to 6 missing series, as the first bar indicates, and one has 29 missing series. On average, countries have about 15 missing series, which equals to 45.5 per cent of missing series per country on average. The figure clearly highlights that missing data are a severe problem for all countries, so that building reliable country-level FCIs is not a feasible option for our sample.

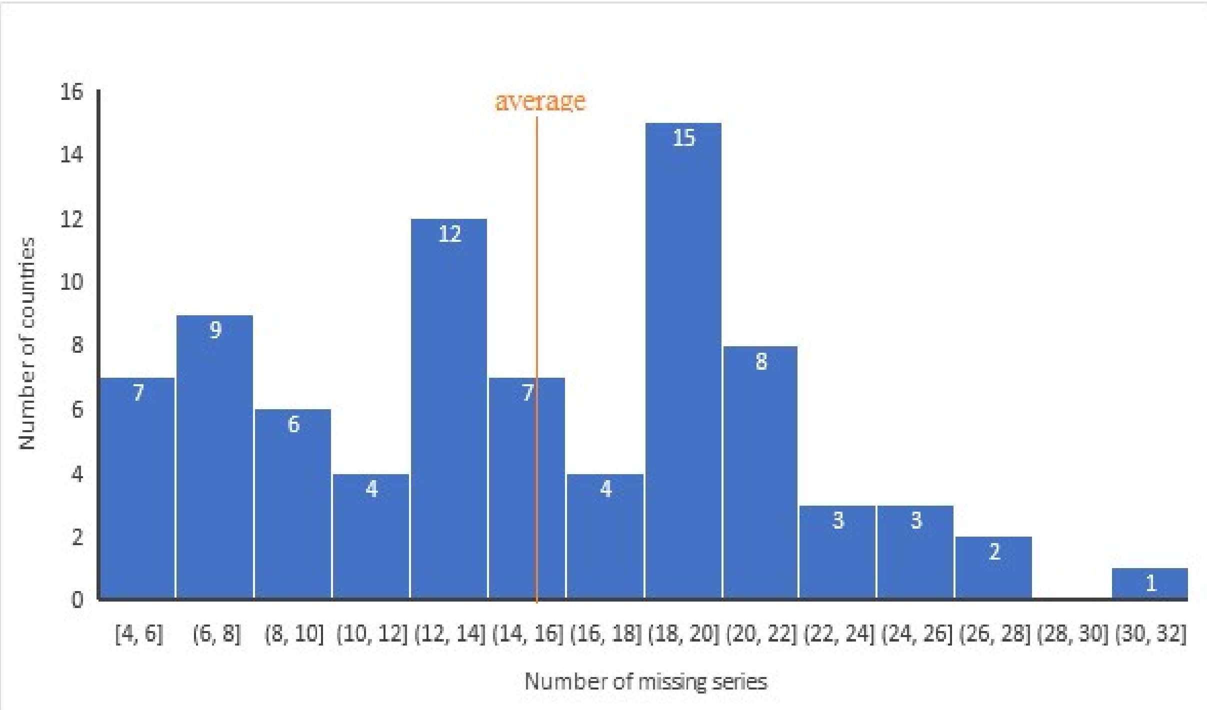

Figure 1 Distribution of the number of missing series in our original sample

Figure 2 summarizes the missing patterns for each series. It reveals that only 9 variables (PRICOM, FUNDUS, CPIYOY, RESERV, RESMOM, DEPRAT, LENRAT, MONYOY and REER) have less than 50 per cent of missing values over all time periods and across all countries. Disaggregating the sample by income class, as shown in Figure 3, we find significant differences regarding the patterns of missing data, since LICs suffer from a significantly larger share of missing observations compared to MICs or HICs economies.

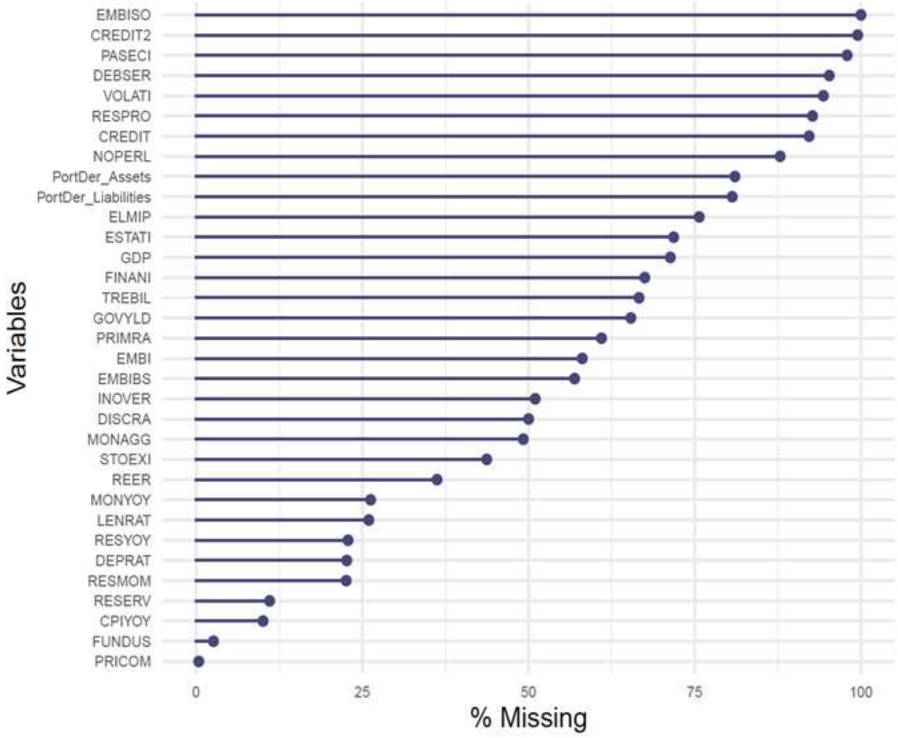

Figure 2 Percentage share of missing observation for the original sample

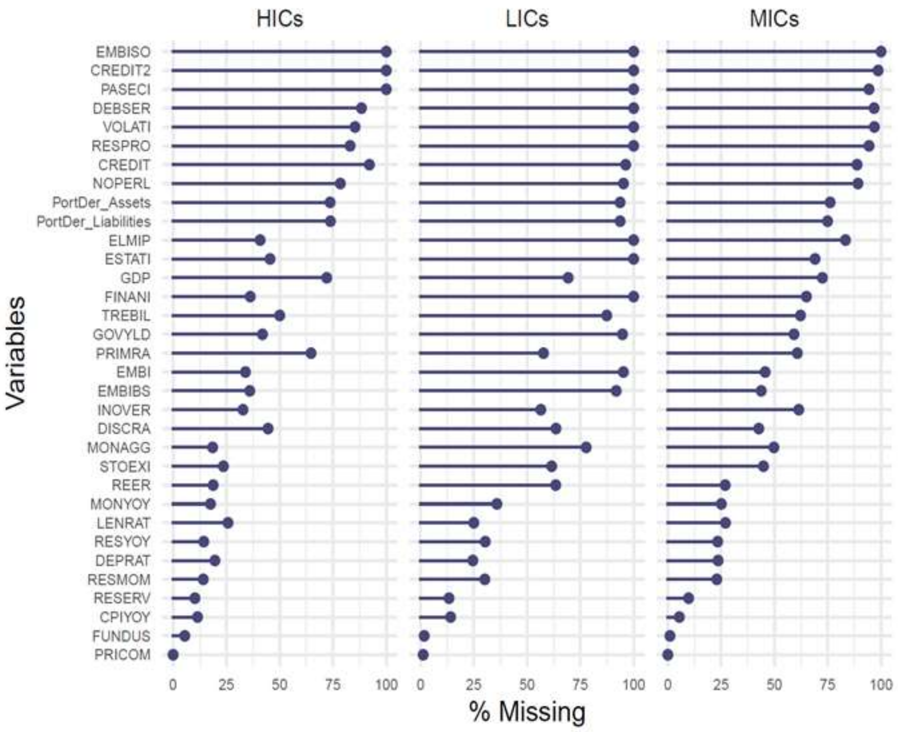

Figure 3 Percentage share of missing observations by income group in the original sample

When analysing the missing data patterns over time, we note that data collection does not seem to have improved much. Figure 4 shows the heatmap of the missing patterns in our sample.

Such heatmaps are a very informative tool to visualise patterns of missingness. They also show that clustering according to certain criteria (e.g., the income group level) can undermine the issue of missing data.

The bright yellow colour corresponds to 100 per cent of missing values, while dark blue indicates no missing information. On the x-axis, we plot the years from 2005 to 2021. Similar to our findings above, we see that some variables are almost fully missing (e.g., CREDIT2) while others only have few missing observations (e.g., PRICOM). As most variables remain highly missing even in the last five years (2016-2021), this suggests that a lot more work and effort must be put into policies that support data generation.

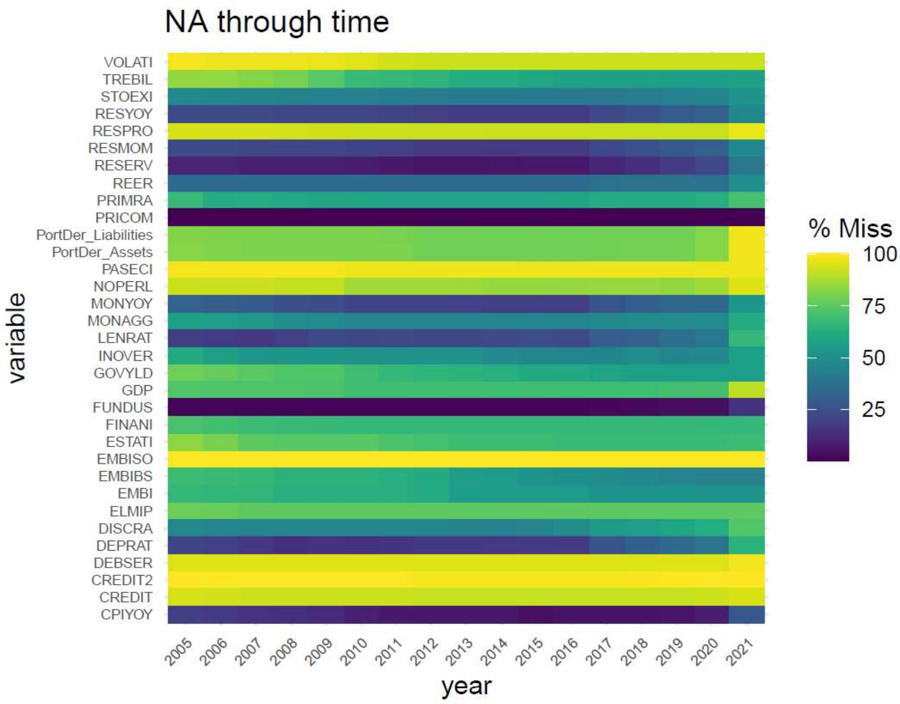

Figure 4 Heatmap of missingness intensity over time from 2005 to 2021

Clustering is, as mentioned, one way to address the problem. Using an illustrative example, Figure 5 outlines the intensity of missing information of each series by country income class. Especially for HICs and MICs, we observe that clustering may reduce the adverse effects of data scarcity. Yet, as already suggested above, in the case of LICs, the issue nonetheless remains substantial.

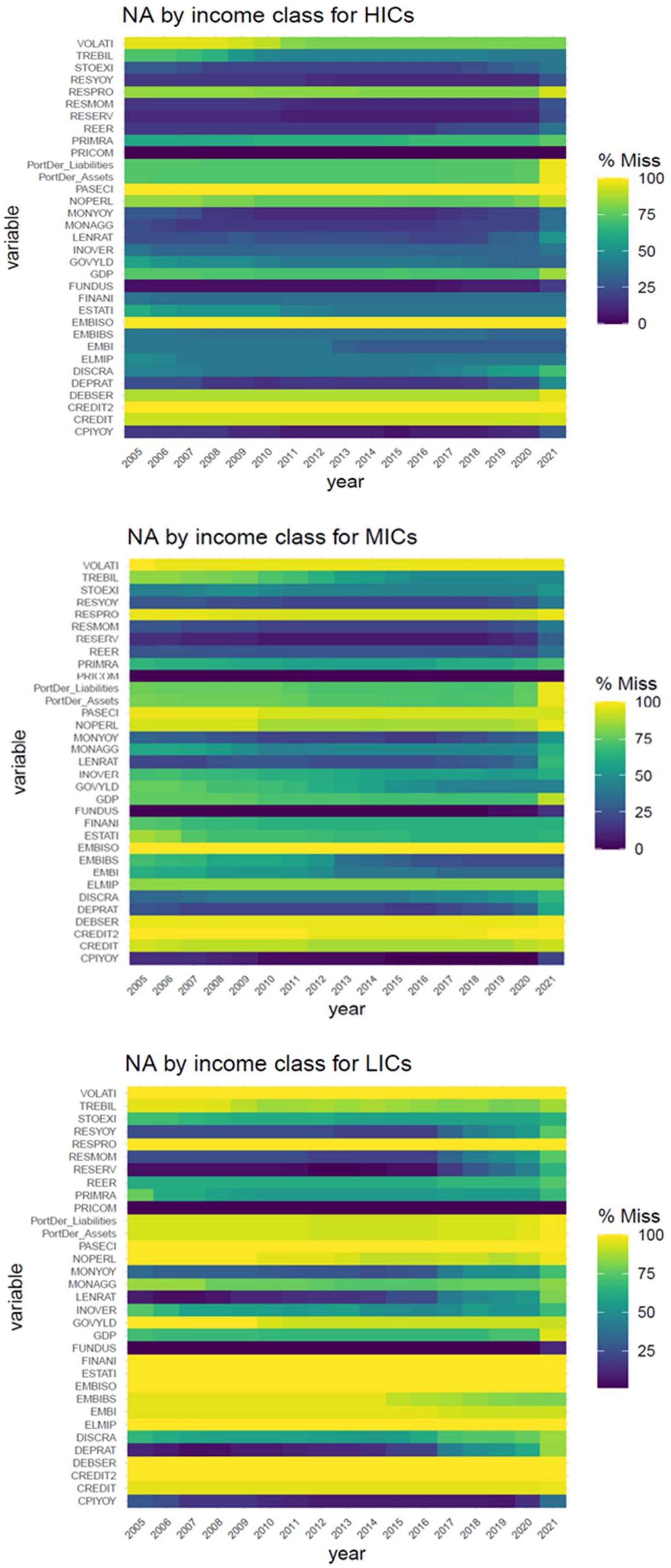

Figure 5 Heatmap of missingness intensity over time and for different income groups

Data processing

With an understanding of the variables employed and specific issues that arise in the context of conducting the analysis for developing countries, we can now move towards describing the data processing in our research. Although macroeconomic and financial variables typically display non-stationary features, factor models usually require stationary inputs. Consequently, each variable should be adequately transformed. Two types of trends were noticed in the data, namely stochastic and deterministic trends. For the former, we used a difference operator. The latter was removed through a nonparametric regression over time for all variables. Variables containing too many missing values (greater than 50 per cent) were removed. Otherwise, missing values were imputed using the iterative principal component analysis (PCA) algorithm (Husson & Josse, 2012). Quarterly variables, however, were reiterated to obtain monthly data. Finally, all variables were rescaled to have 0 mean and unit variance.

Section IV – Methodology

In this section, we first review and discuss the use of factor analysis in the creation of FCIs. Our presentation of the methodology follows.

Literature review on the use of factor analysis to build high-frequency macroeconomic indicators

Factor models

Over the last decades, the analysis of large macroeconomic datasets through dynamic factor models (DFMs) has become increasingly popular. Originally, (Engle & Watson, 1981), (Geweke, 1977), and (Sargent & Sims, 1977) generalised the static exact factor model introduced by Spearman (1904) in the psychology literature to capture dynamics in economic data. Building on the idea that the co-movement of macroeconomic series could be linked to the business cycle (Burns & Mitchell, 1946), several authors postulated that these dynamic exact factor models could summarize the behaviour of major economic aggregates and measure economic conditions describing the business cycle (Geweke, 1977; Sargent & Sims, 1977; Stock & Watson, 1989, 1991, 1993). These early applications mainly focused on the frequency domain and assumed orthogonal idiosyncratic components. More recent work in the frequency domain by Forni et al. (2000) generalises previous DFMs by allowing for correlated idiosyncratic components and admits the approximate factor model of Chamberlain (1983) and Chamberlain and Rothschild (1983) as a special case.

Following the work carried out in the frequency domain, a first generation of DFMs considers exact factor models in the time domain. The exact factor model is, in fact, a low-dimensional parametric model that admits a static representation. Written in its state-space form, the gaussian likelihood of the model can be computed using the Kalman filter and the model estimated by maximum likelihood estimation. Watson and Engle (1983) suggest using a score algorithm, the EM algorithm, or a combination of both for the numerical optimization. Although the estimation can handle irregular data (e.g., missing values, mixed-frequencies, or unbalanced panels), nonlinearities in the parameters estimation historically limited the number of time series that could be managed. Moreover, the model assumes gaussian idiosyncratic components, which imply no cross-correlation across the series and are often considered too restrictive.

Two seminal papers by Chamberlain (1983) and Chamberlain and Rothschild (1983) relax the assumption of no cross-correlation between the idiosyncratic components. Their proposed approximate dynamic factor model allows for mild cross-correlation, and they provide conditions under which the approximate factor model is asymptotically identified. This second generation of DFMs uses nonparametric estimators such as PCA to estimate the approximate factor model. The method can accommodate large datasets but is not applicable to unbalanced panels. One strong advantage of PCA estimators is that the estimated factors are asymptotically consistent and can be treated as data in subsequent regressions. Stock & Watson (2002a, 2002b), Bai and Ng (2002) and Bai (2003) are among the first to popularize this approach in macroeconomics.

A third generation of DFMs integrates the robustness and convenience of PCA in the first generation of state space models. It consists of a two-step estimator where the factors are first estimated via PCA and then used to estimate the parameters of the state space model. More detail on the method and its implementation can be found in Giannone et al. (2008) and Doz et al. (2006, 2011, 2012). This hybrid procedure has the appeal of handling both large scale unbalanced panels and irregular data. Therefore, it is particularly interesting for real time applications, given that the Kalman filtering allows handling missing data and that it can be implemented in real time as individual data are released. For further discussion on "Nowcasting" see Giannone et al. (2008).

At UNCTAD, Bicchetti and Neto (2018) used the two-step estimator described earlier and proposed a first generation of FCIs for a handful of developing countries. Since then, the literature on FCIs has made substantial progress in both academic and policy spheres. Indeed, several public bodies including the International Monetary Fund (IMF) and central banks started to develop their own FCIs with a fair bit of success (Arregui et al., 2018; Brandao-Marques & Ruiz, 2017; International Monetary Fund, 2017; Kapetanios et al., 2018). A special attention was given to econometric techniques that could estimate DFMs while dealing with the changing macro-financial landscape over time, thus yield more stable estimates.

Structural Breaks

Our paper proposes a new generation of FCIs to monitor financial conditions in developing countries. It addresses two key challenges. First, following the strides in measuring FCIs, we propose to take into account the evolution of the macroeconomic conditions over time. We do so by allowing for structural breaks in the DFM using time-varying factor loadings. Second, as described in the previous section, we propose to avoid the data scarcity issue by clustering countries.

The literature on structural breaks in DFMs can be roughly classified in two strands. A first strand of the literature models the evolving financial and macroeconomic conditions through time by introducing nonlinearities. In the context of the construction of coincident indices, the necessity became apparent to allow the index to vary over time according to the business cycle. Kim (1994) and Diebold and Rudebusch (1996) were among the first to suggest incorporating Markov switching behaviour into DFMs to capture time variation. Recent application of Markov switching dynamic factor models to predict the business cycle can be found in Carstensen et al. (2020).

The other strand of the literature deals with time-changing conditions by relaxing the assumption of constant factor loadings. Allowing factor loadings to vary through time is particularly relevant when the true relationships are affected by large structural breaks. Doz and Fuleky (2020) warn that assuming constant loading in such cases may lead to overestimating the number of factors, inconsistent estimates of the loadings, and deterioration of the forecasting performance of the factors. The literature on time-varying factor loadings is growing rapidly and can be synthesised along two main axes.

The first considers that factor loadings are subject to a small number of breaks through time. Testing procedures were developed to identify such breaks. Breitung and Eickmeier (2011) show that strong breaks in the loadings require increasing the number of common factors since two sets of factors are needed to describe the common component before and after the break. They are also among the first to propose tests of the null hypothesis of constant loadings in individual series for either a known or unknown break date. Since then, numerous authors have proposed test to detect structural breaks (Chen et al., 2014; Corradi & Swanson, 2014; Han & Inoue, 2015; Ma & Su, 2018; Su & Wang, 2017; Yamamoto & Tanaka, 2015).

The second strand of literature focuses on factor loadings that are different at each point of time. Stock and Watson (2002a) consider small-amplitude time variations in the loadings. They show that the PCA estimator of the factors is consistent even with certain types of breaks or time variation in the factor loadings. Other relevant papers that model loadings to be different at each point in time include Del Negro & Otrok (2008) and Su & Wang (2017). Del Negro & Otrok (2008) develop a DFM with time-varying coefficients which they estimate using a parametric

Bayesian procedure. Su & Wang (2017) consider a DFM where the factor loadings are a smoothed function of the rescaled time.

The next subsection presents the different models used to propose a new generation of FCIs. Our methodology builds on the seminal work carried out in the DFMs literature as well as its latest developments. Our model refers to the static representation[8] of these DFMs: this approach has the advantage to suit our needs and remain simple to interpret. We also rely on the recent advances in the literature on structural breaks in DFMs to consider time-varying factor models. Specifically, we allow the loadings to change with time either by expressing them as an affine function of a relevant macroeconomic variable or as a smoothed function of the rescaled time. Both approaches have pros and cons which we further elaborate in the next subsection.

Our methodology

As previously stated, factor analysis (and its many variants such as dynamic factor analysis or time-varying factor analysis) is a popular approach to measure financial stress. The aggregated indicator, which gives us the overall level of stress, is what we refer to as the FCI. Whilst each country in our panel has its own idiosyncrasies, we outlined that several systemic or global factors affect national FCIs. Given the systemic and shared nature of financial vulnerabilities of developing economies, we assume that we can cluster groups of countries with similar conditions. The corresponding FCIs – the group FCI – are thus the aggregated value for all the individual countries' FCIs that make up the respective group. We consider several grouping methods, either based on ex-ante information, such as a country's income classification or geographic location, or ex-post classifications, driven by the data as such. For each group, we extract the group FCI as a weighted sum of those of its members. We stress that these group FCIs are not meant as predictor of country-level FCIs for those countries with sufficient data. In fact, if predicting country-level FCIs were the sole goal of the project, an obvious alternative would be to use a regression-type approach, where each country-level FCI would be regressed on all others. However, by pursuing prediction, we would lose the economic interpretation that the clustering provides. In any event, the current work provides a strong basis on which to build sophisticated predictive models. A predictive analysis of the group-level FCI and competing models is beyond the scope of this project and is left for future work.

[8] The dynamic representation of the DFMs captures the dependence of the observed variables on the lags of the factors explicitly, while the static representation embeds those dynamics implicitly.

We provide a general framework for computing the country and group FCIs, which will follow a two-stages approach:

i. In the first stage, we extract the country FCIs.
ii. In the second stage, the countries are clustered, and for each cluster, we extract the group FCI.

Depending on the selected method to extract the factors, it is sometimes possible to merge both stages into a single-stage approach, in which both country and group FCIs are extracted simultaneously. There are certain advantages to this approach. One reason to consider such a ‘‘single-stage estimation’’ is that the estimation of each country’ FCIs may be improved by the knowledge of its group membership and FCI, and vice versa.

Yet, after having implemented this single-stage approach, we have found that the extracted country FCIs were virtually identical to those computed with a two-stages approach. Moreover, we note that a single-stage approach is more difficult to implement, which limits the methodological options for factor extraction and group creation. Another option we have considered is to bypass the first stage where the country-level FCIs are calculated, and compute the group-level FCIs directly from all variables of all countries pooled together. From a statistical perspective, this approach would have the advantage of having lower variance, at the potential cost of greater bias due to country-specific idiosyncrasies that would otherwise be absorbed in the error term, not to mention difficulties in appropriately weighing the variables of the countries when their numbers differ. What’s more, from an economic perspective, it makes sense to first calculate country FCIs as they are the entity which directly relates our research to the existing literature. Though imperfect, they may provide useful insights for the interpretation of the clusters. This stage also allows for rebalancing data gaps across countries as described in the previous section, as well as an easy implementation of alternative methodologies for each of the stages independently. Therefore, we opted for the separation into two-stages, as shown in both the theoretical presentation of this section and the implementation in the computer programme.

In this section, we present the various methods that we have implemented for these two stages:

- **Stage 1**: *i)* static factor analysis, *ii)* conditional time-varying factor analysis, *iii)* and nonparametric time-varying factor analysis,
- **Stage 2**: *i)* ex-ante grouping, and *ii)* ex-post clustering.

Definitions and Notations

We present and define below several quantities and notations used throughout this section. The description of the various factor models draws on Barhoumi et al., 2013.

i	Index for the countries, $i = 1, \dots, n$.
t	Index for the time, $t = 1, \dots, T$.
j	Index for the variables, $j = 1, \dots, p_i$.
k	Index for the groups, $k = 1, \dots, q$.
p_i	Number of observed variables for country i.
$\boldsymbol{Y}_{i,t}$	p_i-vector of observed variables for country i at time t.
$F_{i,t}$	Country-level factor (FCI) of dimension 1 for country i at time t.
$\widehat{\boldsymbol{F}}_t$	Vector of the n estimated country-level factors at time t.
$\{F_i\} \equiv \{F_{i,1}, \dots, F_{i,T}\}$	Country-level factor (FCI) of length T for country i.
$G_{k,t}$	Group-level factor (FCI) of dimension 1 for group $k = 1, \dots, q$ at time t.
$\{G_k\} \equiv \{G_{k,1}, \dots, G_{k,T}\}$	Group-level factor (FCI) of length T for group $k = 1, \dots, q$.
$\{V_{i,t}\}$	Conditioning variable for the time-varying problem, for instance its GDP.
$\boldsymbol{\epsilon}_{i,t}$	p_i-vector of idiosyncratic components for the observed variables for country i at time t.
$\boldsymbol{\lambda}_i$	p_i-vector of factor loadings for the observed variables of country i
$\boldsymbol{\alpha}_{\mathrm{i}}$	q-vector of group-level factor loadings, with only one non-zero element corresponding to the group of the country

Stage 1, Option 1: Static Factor Analysis

For each county, indexed by $i = 1, \ldots, n$, we observe, for time $t = 1, \ldots, T$, a p_i-dimensional vector of financial variables, $\{\boldsymbol{Y}_{i,t} = (Y_{i,t,1}, \ldots, Y_{i,t,p_i})', t = 1, \ldots, T\}$, which is assumed to be standardized, to have finite variance and to be stationary. Furthermore, it is assumed that a single one-dimensional unobserved variable $\{F_i\} \equiv \{F_{i,t}, t = 1, \ldots, T\}$, the *factor*, which, in our context, is the country FCI, captures all linear dependence between a country's observed variables, in the sense that it provides a linear explanation of $\boldsymbol{Y}_{i,t}$:

$$\boldsymbol{Y}_{i,t} = \boldsymbol{\lambda_i} F_{i,t} + \boldsymbol{\epsilon}_{i,t}, \qquad 1)$$

where $\boldsymbol{\lambda}_i = (\lambda_{1,1}, \ldots, \lambda_{i,p_i})'$ is a vector of loadings associated with country i, and $\boldsymbol{\epsilon}_{i,t} = (\epsilon_{i,1}, \ldots, \epsilon_{i,p_i})'$ is a vector of idiosyncratic components that cover the shocks specific to each of the observed variables that is not explained by the country factor. Note that except for the dimensions p_i , which represents the number of observed variables and is specific to each country, we assume that model 1) applies to all countries.

Different sets of assumptions made on the quantities in 1) lead to different models. The simplest set of assumptions yields the static model, which we now present.

The Static Factor Model

ASSUMPTION 1. For all i and t, the factor $F_{i,t}$ is centered, $E[F_{i,t}] = 0$, and has unit variance $E[F_{i,t}^2] = 1$.

ASSUMPTION 2. For all i and t, the idiosyncratic noise $\boldsymbol{\epsilon}_{i,t}$ have mean zero, $E[\boldsymbol{\epsilon}_{i,t}] = 0$, and are orthogonal with diagonal variance-covariance matrix $E[\boldsymbol{\epsilon}_{i,t}\boldsymbol{\epsilon}_{i,t}'] = diag(\sigma_{i,1}^2, \ldots, \sigma_{i,p_i}^2) \equiv \boldsymbol{\Sigma}_{\boldsymbol{\epsilon}_i}$.

ASSUMPTION 3. For all i, t and t', the factor $F_{i,t}$ and idiosyncratic noise $\boldsymbol{\epsilon}_{i,t}$ are uncorrelated, $E[F_{i,t}\boldsymbol{\epsilon}_{i,t'}] = \boldsymbol{0}$.

ASSUMPTION 4. The variables are independent and identically distributed over time, that is, in particular: for all i, t and $t' \neq t$, $E[F_{i,t}F_{i,t'}] = 0$ and $E[\boldsymbol{\epsilon}_{i,t}'\boldsymbol{\epsilon}_{i,t'}] = 0$.

In the DFMs literature, this model is referred to as "static" since the ith factor $\{F_i\}$[9]: does not possess its own time dynamic (because of assumption 4) and the loadings $\{\boldsymbol{\lambda}_i\}$ are not a function of time. In the static model, the country factor alone explains the covariance between the country's observed variables, which is proportional to the magnitude of the related loadings. Despite its simplicity, this model provides a very good approximation to the dynamic method presented in the following subsections, as shown by Doz and Lenglart (1999). When the static factor model is used to approximate a dynamic factor model (DFM), the condition for the convergence of the static estimator to the true parameter of the DFM may differ from those outlined above. Nevertheless, we find that these latter shed light on the properties of the model. The interested reader will find below the references for consistent estimation of a DFM by the approximate static estimator. Under assumptions 1-4, the variance-covariance matrix of $\boldsymbol{Y}_i$ admits the following decomposition:

$$\boldsymbol{\Sigma}_{\boldsymbol{Y}_i} \equiv E[\boldsymbol{Y}_i \boldsymbol{Y}_i{}'] = \boldsymbol{\lambda}_i \boldsymbol{\lambda}_i' + \boldsymbol{\Sigma}_{\boldsymbol{\epsilon}_i}$$

Letting $\boldsymbol{\theta} \in \boldsymbol{\Theta} \subseteq \mathbb{R}^{2p_i}$ collect all parameters of the model $(\boldsymbol{\lambda}_i, \boldsymbol{\Sigma}_{\boldsymbol{\epsilon}_i})$, we adopt the following widely used estimator for $\boldsymbol{\theta}$ as the minimizer of:

$$\widehat{\boldsymbol{\theta}} = argmin_{\boldsymbol{\theta}\in\boldsymbol{\Theta}} \sum_{t=1}^{T} (\boldsymbol{Y}_i - \boldsymbol{\lambda}_i F_{i,t})'(\boldsymbol{Y}_i - \boldsymbol{\lambda}_i F_{i,t}) \quad subject\ to\ \boldsymbol{\lambda}_i' \boldsymbol{\lambda}_i = 1. \qquad 2)$$

In this method, the estimated factors $\{\widehat{F}_{i,t}\}$ are also obtained as the minimizer of 2). (Stock & Watson, 2002b) and (Bai & Ng, 2002) establish the asymptotic properties of this approximate estimator under appropriate assumptions that the interested reader will find therein, and show that this method produces convergent estimators even when the data used are autocorrelated, as in our case. Alternatively, one can use PCA to both estimate θ and extract the factors $\{\widehat{F}_{i,t}\}$. The availability of fast, robust, and consistent numerical methods to estimate the parameters and extract the factors, and the adequacy of the method to model even correlated data – despite its simplicity – makes this model a prime initial candidate for the extraction of the country factors.

Stage 1, Option 2: Dynamic Factor Analysis with Conditional Time-Varying Loadings

We now consider time-varying factor models, where the loadings are allowed to change with time. They are particularly suited for developing countries that exhibit at times radical regime changes over the period of this research. We propose to adapt a model introduced by Park et al.

[9] We use 'factor' to designate the whole factor series or any of its elements, depending on the context.

(2009): specifically, each country's loadings are now expressed as an affine function of one of its observed variables, such as its GDP, which we denote by $\{V_{i,t}, t = 1, \dots, T\}$. This variable is thus removed from the pool of observed variables. The model becomes:

$$\boldsymbol{Y}_{i,t} = \left(\boldsymbol{\alpha_i} + \boldsymbol{\beta_i} V_{i,t}\right) F_{i,t} + \boldsymbol{\epsilon}_{i,t}, \qquad 3)$$

where $\boldsymbol{\alpha}_i$ is a p_i-vector of country i's *loading intercepts* (corresponding to the static loading of model 1)), and $\boldsymbol{\beta_i}$ is a p_i-vector of country i's *slope parameters*. The assumptions of the static model still apply. The same estimator is used as before, with the addition of a penalization for large values of $\boldsymbol{\beta}_i$:

$$\widehat{\boldsymbol{\theta}} = argmin_{\boldsymbol{\theta}\in\boldsymbol{\Theta}} \sum_{t=1}^{T} (\boldsymbol{Y}_i - \left(\boldsymbol{\alpha_i} + \boldsymbol{\beta_i} V_{i,t}\right) F_{i,t})' (\boldsymbol{Y}_i - \left(\boldsymbol{\alpha_i} + \boldsymbol{\beta_i} V_{i,t}\right) F_{i,t}) + \lambda \left|\left|\boldsymbol{\beta}_i\right|\right|_2 \; subject\ to\ \boldsymbol{\lambda}_{\boldsymbol{i}}' \boldsymbol{\lambda}_{\boldsymbol{i}} = 1, \qquad 4)$$

where the penalization factor λ affects the magnitude of the estimated $\widehat{\boldsymbol{\beta}}_i$. We conjecture that this penalization makes the model identifiable, the theoretical proof of which must be addressed in future research. Due to the modification of the loadings, computing the estimator 4) is not as straightforward as the previous one (eq. 2), and currently no software is readily available to that end. Drawing on the algorithms used to solve eq. 2), we developed an ad-hoc programme specifically for this task. Its ability to estimate the model parameters has been thoroughly tested on simulated data from the assumed model (eq 3), which validated empirically our aforementioned conjecture. Further work may include the fine-tuning of the parameter λ and studying the theoretical properties of the estimator.

Stage 1, Option 3: Dynamic Factor Analysis with Nonparametric Time-Varying Loadings

In this model, we additionally consider loadings that vary with time, but we now model them as non-parametric, non-negative functions, which is more flexible than the above conditional time-varying method. This allows to smoothly absorb the country shocks. The model becomes

$$\mathrm{Y}_{\mathrm{i,t}} = \boldsymbol{\lambda}_{\mathrm{i,t}} \mathrm{F}_{\mathrm{i,t}} + \boldsymbol{\epsilon}_{\mathrm{i,t}}. \qquad 5)$$

where $\boldsymbol{\lambda}_{i,t} = \left(\lambda_{i,t1}, \dots, \lambda_{i,tp_i}\right)'$ is allowed to vary with time. To obtain a consistent estimate of $\boldsymbol{\lambda}_{i,t}$, we assume that it is a smoothed function of the rescaled time, i.e.

$$\boldsymbol{\lambda}_{i,t} = \boldsymbol{\lambda}_i\left(\frac{t}{T}\right).$$

The assumptions of the static model still apply. To estimate $\boldsymbol{\lambda}_i$ and F_t, we follow the methods in Su & Wang (2017). For a given index i, we define the estimates $\boldsymbol{\lambda}_{i,r}$ and $Z_{i,t}$ as the solution to the following weighted least squares problem:

$$\min_{\boldsymbol{\lambda}_{i,r},\{F_{i,t}\}_{t=1}^{T}} \sum_{t=1}^{T} \| \mathbf{Y}_{i,t} - \boldsymbol{\lambda}_{i,r} F_{i,t} \|_2^2 K_{h_i}\left(\frac{t-r}{T}\right), \qquad 6)$$

for $r = 1,2,\dots,T$. We write $K_h(x) := h^{-1}K(x/h)$, where $K\colon \mathbb{R} \to \mathbb{R}^+$ denotes a kernel function and h is a bandwidth parameter. This time-varying factor model can be seen as rolling PCA: indeed, problem 6) can be written as

$$\min_{\boldsymbol{\lambda}_{i,r},\{Z_{i,t}^{(r)}\}_{t=1}^{T}} \sum_{t=1}^{T} \| \mathbf{Y}_{i,t}^{(r)} - \boldsymbol{\lambda}_{i,r} F_{i,t}^{(r)} \|_2^2, \qquad 7)$$

where $\mathbf{Y}_{i,t}^{(r)} := \sqrt{K_{h_i}\left(\frac{t-r}{T}\right)}\,\mathbf{Y}_{i,t}$ and $F_{i,t}^{(r)} := \sqrt{K_{h_i}\left(\frac{t-r}{T}\right)}\,F_{i,t}$. Thus, to estimate the model, we firstly maximize the typical PCA problem 7) with respect to $\boldsymbol{\lambda}_{i,r}$ and the local factor, $F_{i,t}^{(r)}$. The estimated local factors $\hat{F}_{i,t}^{(r)}$ is $\sqrt{T}$ times the largest Eigenvalue of the matrix $\left(\mathbf{Y}_{i,t}\right)_{t=1}^{T}$ and $\hat{\boldsymbol{\lambda}}_{i,r} = \sum_{t=1}^{T} \hat{F}_{i,t}^{(r)}\, \mathbf{Y}_{i,t}^{(r)} / \left(\sum_{t=1}^{T} \hat{F}_{i,t}^{(r)2}\right)$. Once the loadings have been estimated, in a second step, we extract the factors as $\hat{F}_{i,t} = \left(\hat{\boldsymbol{\lambda}}_{i,t}^{\top}\hat{\boldsymbol{\lambda}}_{i,t}\right)^{-1}\hat{\boldsymbol{\lambda}}_{i,t}^{\top}\mathbf{Y}_{i,t}$.

Further details for the estimation of the model are in the annex. The interested reader will find more information on this estimator, including the assumptions for its convergence, in (Su & Wang, 2017).

Second Stage: Group-level Model

In the second stage, it is assumed that n country factors have been estimated. For each country $i = 1,\dots,n,$ we denote by $\{\hat{F}_i\} \equiv \{\hat{F}_{i,t}, t = 1,\dots,T\}$ the estimated factor series, and for a time t, $\hat{\boldsymbol{F}}_t \equiv \left(\hat{F}_{1,t},\dots,\hat{F}_{n,t}\right)'$ denotes the n −vector of country-level factors. Based on these estimated factors, we now intend to group countries together and compute the corresponding group factors, based on one of two strategies: the first approach is to group the countries based on ex-ante defined groups. For example, the countries can be grouped in a function of their geographic location or income classification. Different grouping strategies will lead to different group factors, hence there remains an inherent subjectivity in the groups chosen for the analysis. Alternatively, we propose an ex-post grouping method in which we automatically group the countries based on the similarity of the country factors themselves, using an ad-hoc algorithm that we will refer to as *automatic clustering*. These groups are created in a way that they maximise the similarity between the loadings of the groups' members, as we now explain.

For each of the q groups indexed by $k, k = 1, \dots, q$, we want to find a group factor series $\{G_k\} \equiv \{G_{k,1}, \dots, G_{k,T}\}$, henceforth simply called 'group factor' or 'group FCI', that can best explain the covariance between the country factors of the $\mathrm{g_k}$ countries that comprise the group, where $\{g_k, k = 1, \dots, q\}$ satisfies $\sum_{k=1}^{q} g_k = n$. This reminds of the first stage, where, for each country, we defined its country factor to be the variable that best explained the covariance between this country's observed variables.

Stage 2, Option 1: Grouping by Ex-ante Groups

When the groups are defined ex-ante, we propose the following second-stage factor model

$$\hat{F}_{i,t} = \boldsymbol{\alpha}_i^{\top} \mathbf{G}_t + u_{i,t} \qquad 8)$$

where $\mathbf{G}_t \coloneqq (\mathrm{G}_{1,t}, \dots, \mathrm{G}_{q,t})^{\top}$ is a q-dimensional latent group-level factor and $\boldsymbol{\alpha}_i$ $:= (\alpha_{i,1}, \dots, \alpha_{i,q})^{\top} \in \mathbb{R}^q$ is a q-vector of group-level loadings with only one non-zero element corresponding to the pre-specified group of country i. The country factors of each group $k = 1, \dots, q$ are therefore modelled using a static factor model, which yields, for each group, a group-level factor and the related group-level loadings which are estimated using the estimator 2). With $\{u_{i,t}\}$ replacing $\{\epsilon_{i,t}\}$, the assumptions of the static model are satisfied (since they were assumed in the first stage), and, given the values $\{\hat{F}_{i,t}\}$, the group-level factor can be extracted. The value of the loadings can help determine whether the countries indeed fit well within their group.

Stage 2, Option 2: Ex-Post Grouping by Automatic Clustering

This approach yields group FCIs which are the most representative of the financial conditions of its members. It is important to note that the clusters will not necessarily match geographical regions but may bring out new network patterns. This automatic clustering, however, poses a great methodological challenge: each estimated FCI at a group level depends on the country members of the group, and, conversely, the membership of each country to a particular group depends on the estimated group-level FCIs. Our answer to this challenge is to consider the country FCIs resulting from the First Stage analysis, $\boldsymbol{F}_t = \left(F_{1,t}, \dots, F_{n,t}\right)'$, to be themselves driven by a *sparse factor model*, as follows:

$$\hat{F}_{i,t} = \boldsymbol{\alpha}_i^{\top} \mathbf{G}_t + u_{i,t} \qquad \|\boldsymbol{\alpha}_i\|_0 = 1, \qquad 9)$$

where $\mathbf{G}_t \coloneqq \left(\mathrm{G}_{1,t}, \dots, \mathrm{G}_{q,t}\right)^{\top}$is a q-dimensional latent factor and $\boldsymbol{\alpha}_i :=\left(\alpha_{i,1}, \dots, \alpha_{i,q}\right)^{\top} \in \mathbb{R}^q$. We let $\|\cdot\|_0$ denote the ℓ_0-norm, which is defined as the number of non-null elements of a vector, i.e. $\|\mathbf{x}\|_0 = \sum_{l=1}^{q} \mathbb{1}(x_l \neq 0)$, for any $\mathbf{x} \in \mathbb{R}^q$. We assume that $F_{i,t}$ and $\boldsymbol{G}_t$, $\boldsymbol{\epsilon}_{i,t}$, and $u_{i,t}$ are zero-mean with finite variance.

This hierarchical structure allows to separate the information into clearly identified components. At the country-level, the information is separated into a component common to all variables, $F_{i,t}$, and variable-specific residual information. The country-level factors $F_{i,t}$ can then be separated into a component common to all countries, G_t, and an idiosyncratic factor, $u_{i,t}$, which is specific to each country. Finally, we restrict the "ℓ_0-norm" $\|\boldsymbol{\alpha}_i\|_0$ to be equal to 1. For a particular country i, this constraint ensures that only one component of the vector $\boldsymbol{\alpha}_i$ is non-null, and therefore that only one of the q factors – the one corresponding to the non-null element of $\boldsymbol{\alpha}_i$ – exerts an influence on this country's observed financial variables $\{\mathbf{Y}_{i,t}\}_{t=1}^{T}$. In effect, the position of the non-null factor in the q −vector $\boldsymbol{\alpha}_i$ determines as to which of the q groups the country belongs. A group K_l, $l = 1, \dots, p_l$, is then determined by all countries for which the corresponding loading is non-null, that is, $K_l = \{i \in \{1, \dots, n\} | \alpha_{i,l} \neq 0\}$.

To summarize, the model results in a country-level factors $F_{1,t}, \dots, F_{n,t}$, specific to the country, and group-level factors $G_{1,t}, \dots, G_{q,t}$, common to a group of countries. Accordingly, we call variable $\boldsymbol{\lambda}_i$ the country-level loadings and variable $\boldsymbol{\alpha}_i$ the group-level loadings. The group-level loadings are useful as they allow to evaluate to which extent the group-level factors affect the country-level factor, and their magnitude is therefore a measure of similarity between the country's FCI and its group. Further details for the estimation of the model can be found in the annex.

Choosing the number of clusters

The number of clusters can be determined by examining the explained variance across nested models ("elbow method"), in addition to economic and interpretability considerations. In our application, this number has been set to 5. As shown in the scree-plot of Figure 6, a larger number of clusters only slightly increases the overall explained variance.

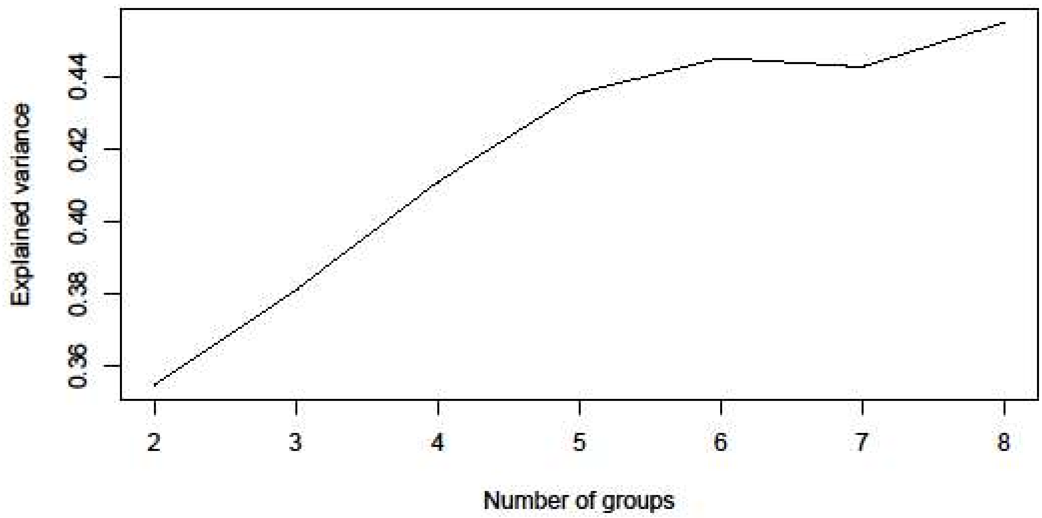

Figure 6 Explained variance of the model as a function of the number of groups q, with a visible "elbow" at $q = 5$ and, to a lesser extent, $q = 6$.

Further Remarks and Model Extensions

Matters of Identifiability

The above models are only identifiable up to the sign of the factors and their respective loadings: for instance, for model 1), we have that $\boldsymbol{\lambda}_i F_{i,t} = (-\boldsymbol{\lambda}_i)(-F_{i,t})$, and similarly for model 5). To decide on the sign of the factor, we particularly look at the GFC. All the countries in our panel show both a large and very specific FCI variation during this episode. We then set the sign of the factors such that this variation corresponds with a negative shock, e.g., a decrease of the FCI and not an increase.

Extension to Stage 1: Dynamic representation

While we do not expect vastly different results, a possible extension in the first-stage analysis is to add time dynamics to the country factors in the manner of Doz et al. (2006) and Giannone et al. (2008), resulting in Dynamic Factor Models, which have recently become popular in the macroeconometric literature. This has not been implemented as the static model is already capable of modelling correlated factors, as previously discussed and showed by Doz & Lenglart (1999), and it was deemed more important to allow for time-varying loadings.

Extension to Stage 2: Ensemble Learning

Our methodology forces each country into one and only ex-ante group or ex-post cluster. The loadings indicate the representativity within the cluster. While this approach facilitates the use and the interpretation of the cluster FCIs, it is also possible to allow for some flexibility in the way in which countries map with clusters. An idea would be to consider an ensemble of K groupings that all have their merit, based on macroeconomic analysis and/or driven by the data. One can then gather, for each country $i = 1, \ldots, n$, the K different factors of its group for each of the K different groupings to nuance the final classification of the country. This K vector can then complement the country factor itself to provide a more general picture of the country's financial conditions, and, potentially, provide new insights to the issue of missing data.

Section V – Results

Comparing ex-ante grouping with ex-post clustering

The ex-ante and ex-post approaches to clustering

For statistical and economic purposes, the United Nations generally classifies countries using three main approaches, which respectively relate to geography, income, and vulnerabilities for which a specific political mandate has been formulated at the international level (namely whether the country is a Small Island and Developing State, a Least Developed Country or a Landlocked Developing Country)[10]. The same tridimensional framework is applied in other International Organisations such as the IMF and the World Bank with few adjustments. It is well-established that these overarching categories provide an intuitive and convenient background against which countries' economic situations and progress can be assessed and synthetised, allowing for quick and sound policy action.

However, countries can be classified into a much broader variety of economic and social categories beyond these official classifications, such as, for example, their trade and/or financial openness, their integration into free-trade zones, currency unions or Global Value Chains (GVC) etc. There is naturally a plethora of dimensions that one can contemplate, the relevance of which varies with the specific area of research. These different affiliations are not mutually exclusive, and their overlapping can be key in understanding domestic economies and coming up with relevant clustering at the global level.

Given the objective of this research to deliver relevant clustered financial conditions indicators, the question then arises: "what is the most relevant way to group developing countries when it comes to financial conditions?" As our aim is to make up for data scarcity by grouping developing countries with similar financial conditions together, this question also implies addressing the thorny issue of financial linkages and transmission channels across developing countries.

For most of us, the first answer which comes to mind may be that of the geographic breakdown. We all have in mind major financial crises which went down in economic history through a regional labelling such as the 1997 "Asian Financial Crisis" or the 1982 "Latin American Debt

[10] For further information on these official classifications, see https://unstats.un.org/unsd/methodology/m49/

Crisis". The geographic breakdown also seems convenient as it refers to an official UN classification, which most policy makers and practitioners are familiar with. Interdependence across countries is often examined through a geographic lens, and this may be explained by the heritage of trade and trade theories, in which physical distances[11] and regional integration play major roles. This paper therefore presents FCIs built upon this breakdown and in line with the appropriate UN classifications, including those related to SIDS and LDCs.

However, even before examining the results in greater detail, it appears as though the geographic breakdown may not be the most relevant approach. The 1982 crisis, for example, did not propagate throughout Latin America following a domino effect involving bilateral or regional transmission channels in the trade or finance realms. Instead, it was triggered by foreign commercial banks which drastically reduced or halted new lending to Latin America in the wake of Mexico's sovereign default. Commercial banks assumed that other countries in the region were doomed to the same fate, given their similar debt ratios and development models, mostly based on import substitution industrialisation. Sources of financing for developing countries have drastically changed ever since, shifting from commercial banks to financial markets and securitisation. Financial crises no longer result, as in 1982, only from excessive public debt and the subjective interpretation of economic data by commercial banks, but they are also triggered by investors' self-fulfilling anticipations and herd behaviour in financial markets. As a result of this major shift, financial crises in developing countries have been more frequent since the late 1990s than during the previous decades but, on average, not as deep and systemic (Raffinot & Ferry, 2019).

Approaching financial conditions through countries' levels of income could be another viable option for the ex-ante grouping. GDP per capita, which provides insights on countries' developmental stage and progress in structural transformation, should capture, to a certain degree, countries' financing needs but also available financing options. Depending on their level of income, developing countries embrace different financing strategies within a limited range of alternatives. Low-income countries do not have access to some private financial markets but in turn, they can benefit from flows of concessional finance for which high- and middle-income countries are not eligible. On this note, the fact that access to concessional finance, including Official Development Assistance (ODA), as well as financial assistance and debt relief programmes from international organisations, is determined by GDP per capita,

[11] According to the gravity model of international trade (Tinbergen, 1962), bilateral trade flows vary with distances between countries, in addition to economic sizes.

provides an additional argument in favour of aggregating financial conditions indicators by income. We have therefore opted to use the UN income classifications in this analysis as well.

Naturally, other pre-existing classifications might be considered for specific research purposes. However, this paper intends to go beyond mere ex-ante approaches. It proposes, in addition to the conventional groupings by regions and income, an ex-post clustering based on the intrinsic similarities between the country-level financial conditions indicators. The main advantage of this strategy is that it does not impose a pre-defined, and potentially biased, reading of the data. Instead, it lets the data "speak for themselves", which is particularly relevant in view of the inherent instability of financial markets. This quantitative analysis hence aims to shed light on the undocumented linkages between developing countries' financial conditions, which will, in turn, end up contributing to formulating a more comprehensive framework for their understanding.

Analysis of loadings' distributions across the three grouping methods

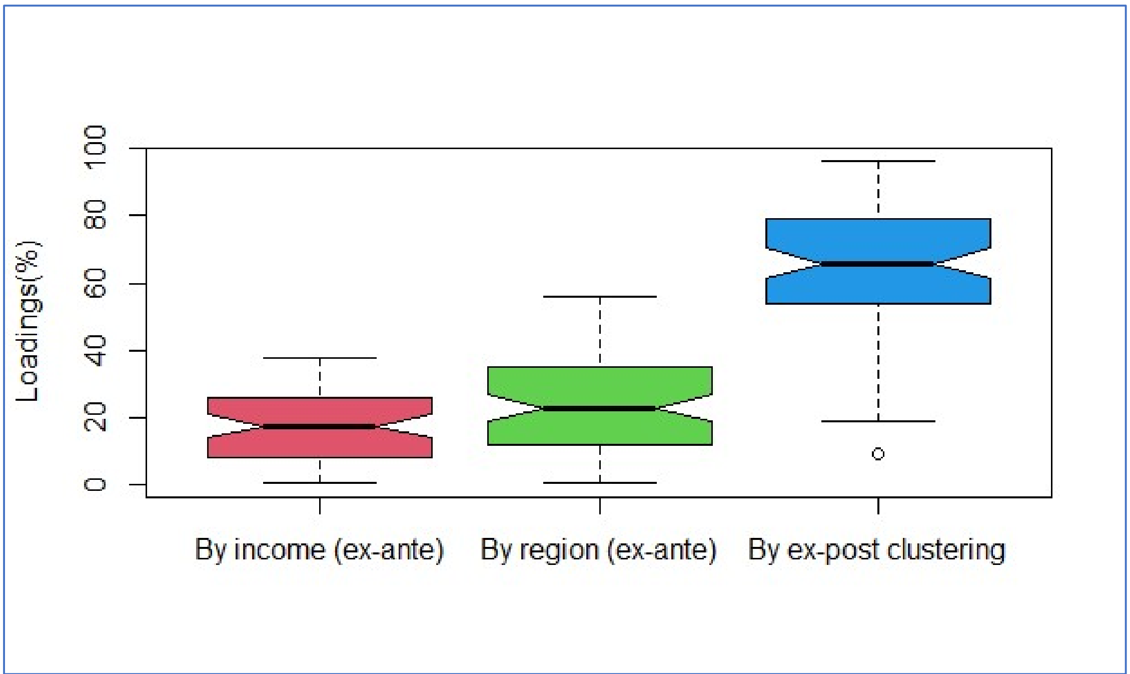

Figure 7 Loadings distributions across the different clustering methods with fixed loadings

The examination of the country loadings resulting from the respective clustering methods, confirms the reservations we presented on the ex-ante classifications and the superiority of the ex-post approach. Figure 7 presents the distributions of loadings for each clustering method in boxplots. As a reminder, loadings measure how well countries fit into their respective group:

the closer to 1 (or 100 per cent), the better represented the country (and conversely the closer to 0). The better representation of countries in the ex-post clustering compared with the ex-ante groupings is blatant. Loadings in the former are systemically higher than in the latter, and this gap is statistically significant: three-fourth of the countries have loadings above 54 per cent with the ex-post clustering, whereas all countries' loadings range below 38 per cent and 56 per cent with the income and geographic groupings respectively. As the detailed distribution graphs in Annex IV show, the good representation holds for the five retained clusters: for each one of these, only very few countries exhibit loadings below 50 per cent. In addition to loadings being organically lower, the ex-ante methods come with significant quality gaps across their categories, which requires more prudence in the interpretation: for example, Asian countries seem more well-represented by their geographic regions than those in sub-Saharan Africa.

These findings are important as they point to very strong similarities and differences between developing countries' financial conditions, which supersede their commonalities in terms of geographic location and level of income. To our knowledge, such results have not been established to date in the existing literature, but they have significant implications for policymaking: it means, plainly put, that when it comes to financial conditions and the forecasting of financial stress and/or crises, a developing country may not necessarily learn from the situation and experience of its immediate geographic neighbours or other countries in the same income group. However, understanding the reasons underlying the groupings of the ex-post classification approach remains challenging. Further below, we explore the factors bringing together the countries in each cluster by first examining the differences across the respective FCIs calculated with fixed loadings, in particular in terms of shocks captured, and second, by corroborating the clusters with external macroeconomic data, including on Global Monetary Conditions (GMCs) and commodity prices, which have identified as two main drivers of financial conditions in both developed and developing countries (Davis et al., 2021; Miranda-Agrippino & Rey, 2021).

The cluster FCIs for ex-ante income groups and geographical regions are presented in Annex IV. They represent the best aggregate indicators, should practitioners desire or need to use these classifications. They provide the best average picture of how financial conditions evolve and respond to external shocks in these *de jure* categories. As aforementioned, our program allows to adopt any other ex-ante classification, as the user sees fit.

Economic findings from the ex-post clustering

Our results indicate that certain commonalities regarding financial stability and vulnerability prevail across the entire sample. On a global level, we find, unsurprisingly from a Minskian point of view, that the period of this research was marked by large up- and downswings of financial conditions. Yet, at the same time, our analysis also reveals distinct patterns and features for each country cluster, which can serve as the basis for deriving more targeted policy measures.

The result section starts with a descriptive geographical breakdown of the identified clusters and a note on income classification data. It then proceeds to briefly explaining overarching trends and features across and within clusters, before going into more detail in explaining each group.

Geographic fragmentation

The analysis of 76 developing and emerging countries identified five different clusters with similar patterns of financial vulnerability. Figure 8 provides an overview of where the countries, which belong to a common cluster, are globally located. It is interesting to note that the data reveal a high degree of regional fragmentation, which varies depending on the level of regional economic integration, insertion into global financial markets, trade patterns, as well as economic diversification. We will refer to the specific characteristics of each cluster in greater detail further below. First, examining the regional distribution of clusters, we find that the African continent is the most fragmented one, with all five clusters being represented here. It is followed by Latin America, albeit most economies here belong either to group 1 or 2. The most homogenous region in terms of its cluster-diversity is East Asia, as most economies fall into group 1.

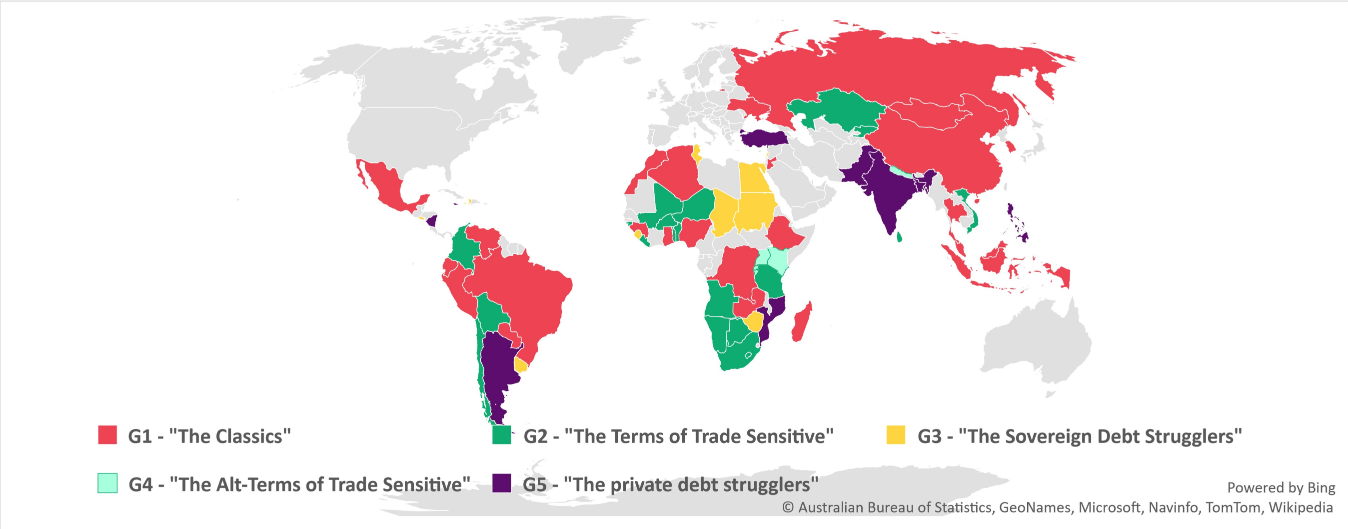

Figure 8 Distribution of countries across the five clusters[12]

Table 2 provides a more detailed overview of the cluster distribution by geographic regions and the associated average loadings. As evident from the map, we see that, overall, close to 40 per cent of economies are in group 1 and around 30 per cent were clustered within group 2. These groups thus make up the largest chunk of the sample. An interesting difference in terms of the geographic distribution is the fact that, while group 1 contains countries from across the world – with some higher representation of the East Asia Pacific (EAP), Latin America and the Caribbean (LAC), and Sub-Saharan African (SSA) regions – group 2 is mostly dominated by SSA economies. The groups 3-5 contain fewer countries. Of these, group 5 is geographically the most diverse, whereas group 3 is primarily made up of LAC and Middle East and Northern African (MENA) economies, and group 4 almost exclusively contains SSA economies (more specifically, countries from the Eastern African Community). The average load factors are high across the groups, which indicates a good fit of the model.

[12] Saudi Arabia and Tajikistan were excluded from this map, as their loadings are lower than 20% (respectively 18.9% and 9.4%) which obviously signals inadequate representation in their clusters.

Clusters	EAP	ECA	LAC	MENA	SAS	SSA	Total
G1							
Number of countries	8	2	6	3	0	10	29
Mean of Loadings	22.8%	5.3%	14.3%	5.8%	0.0%	20.1%	68.3%
G2							
Number of countries	1	2	4	1	1	13	22
Mean of Loadings	1.6%	4.4%	11.3%	0.9%	2.4%	40.3%	60.8%
G3							
Number of countries	0	0	3	3	0	4	10
Mean of Loadings	0.0%	0.0%	18.0%	21.8%	0.0%	27.6%	67.4%
G4							
Number of countries	0	0	0	0	1	4	5
Mean of Loadings	0.0%	0.0%	0.0%	0.0%	15.8%	54.6%	70.3%
G5							
Number of countries	1	2	3	0	3	1	10
Mean of Loadings	5.9%	8.0%	21.6%	0.0%	19.2%	5.8%	60.5%
Total Number of countries	**10**	**6**	**16**	**7**	**5**	**32**	**76**

Table 2 Distribution of the clusters across geographical regions

Clusters across income classification

Table 3 provides the data regarding the cluster distribution by income groups and the associated average loadings. As in the case of geographic distributions, we find that the clusters are diverse. Group 1 contains a higher share of HICs and MICs, whereas the distribution in groups 2 and 4 is tilted towards LICs. Group 3 and 5 predominantly consist of MICs, even though some HICs and LICs are also represented.

Clusters	1.High Income	2.Middle Income	3.Low Income	Total
G1				
Number of countries	12	12	5	**29**
Mean of Loadings	32.2%	27.4%	8.7%	**68.3%**
G2				
Number of countries	7	6	9	**22**
Mean of Loadings	17.95%	14.12%	28.70%	**60.78%**
G3				
Number of countries	2	5	3	**10**
Mean of Loadings	13.9%	33.1%	20.4%	**67.4%**
G4				
Number of countries	0	1	4	**5**
Mean of Loadings	0.0%	17.7%	52.7%	**70.3%**
G5				
Number of countries	2	6	2	**10**
Mean of Loadings	15.6%	38.3%	6.7%	**60.5%**
Total Number of countries	**23**	**30**	**23**	**76**

Table 3 Distribution of the clusters across income groups

Same story, different impacts

When analysing the FCIs of all clusters, as presented in figure 8, it becomes evident that boom-and-bust patterns are at the heart of the story. Most clusters had to deal with substantial up- and downturns of financial conditions in their economies, albeit to different degrees and, at times, with divergent trajectories. As international speculators place their bets in the global casino of international finance, Minskian self-reinforcing sentiments and herd behaviour generates price bubbles across financial asset classes. Once the music stops and speculators turn their back, the downturns set in. Over the past 15 years, this has been the most obvious pattern *across* the sample. Consequently, stable financing conditions, which are a prerequisite for investments and therefore development, were largely absent in the developing world.

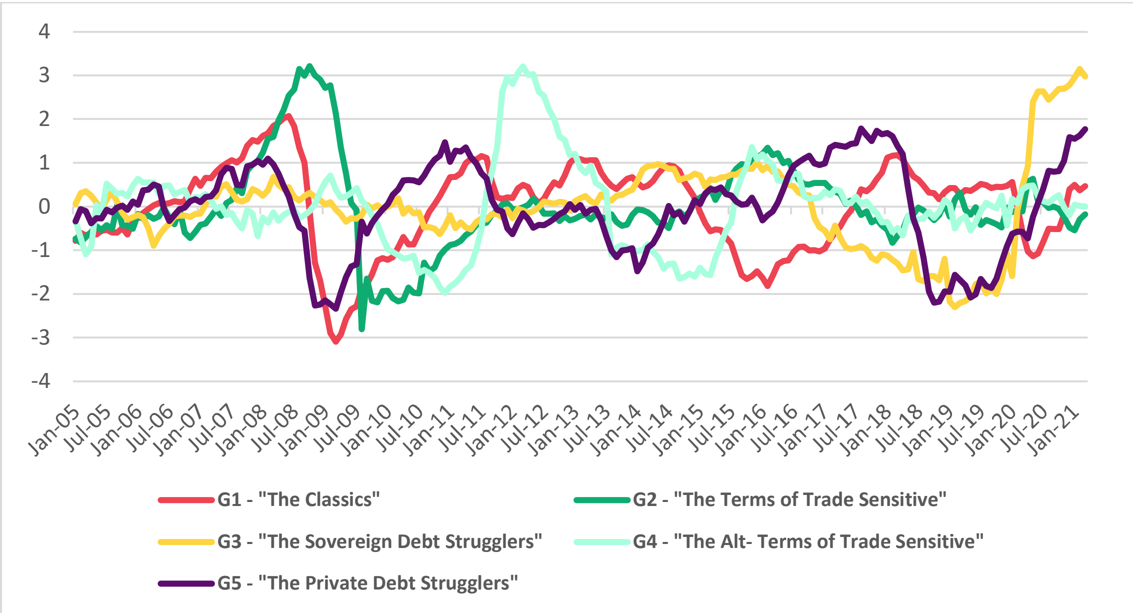

Figure 9 Cluster FCIs between Jan 2005 and March 2021

Despite this common feature, we do observe differing tendencies between the groups. Each one has specific characteristics which makes it more vulnerable to some shocks compared to others. Overall, we identify two main groups (group 1 and 2) and three variations (groups 3-5).

We refer to group 1 as the “classics”, since they represent the most common characteristics regarding financial instabilities in developing and emerging economies, i.e., a high dependence on commodity prices and global monetary conditions. This makes them particularly susceptible to the vagaries of speculative capital flows, especially in form of carry trades that dampen their competitiveness. An appreciation of the US-Dollar is a problem to this group, as it induces capital flight[13]. Group 2, the other main group, contains the “terms of trade sensitive” economies. In this group, the effects of global monetary conditions and commodity prices are the opposite of those in group 1. Financial conditions are eased via improving terms of trade which outweigh the effects of capital flight to safety. This group overall benefits from a stronger dollar and lower oil prices through imports.

Group 3 to 5 are variations of both main groups with a particular vulnerability in public debt, private debt, or gold prices. Group 3, the “sovereign debt strugglers”, includes economies with very high shares of public debt in GDP. Moreover, in these countries, political uncertainty, social unrest or even wars over the last decades have compounded risk premia. The main difference to group 1 is that the high share of public, as opposed to private debt, makes financial conditions over time more stable. Group 4 is the “alt-terms of trade sensitive” group. This group differs from group 2 essentially before 2013, with a delayed impact of the GFC and, more importantly, a higher sensitivity to precious metal prices, in particular gold. The sensitivity to gold, however, waned over time and the FCI converge with that of group 2, the “terms of trade sensitive”. Finally, group 5 is the group of the “private debt strugglers”. It is an extreme version of the “classics” with similar trends but much higher volatility. As “the classics”, capital markets in “the private debt strugglers” group are subject to carry trades and huge reversals of capital flows. Yet, their very high share of private foreign-currency denominated debt, excessive leverage in the private sector, and low stocks of foreign reserves leaves them much more vulnerable to changes in market sentiments. As speculative investors start to flee their capital markets, national currencies start to dive. High inflation, sharp depreciations, waves of non-performing loans, bankruptcies and, ultimately, sovereign defaults are a recurring outcome. The recurrence of financial crises emanating from the private sector progressively dents the long-term resilience of the government against debt distress. In what follows, we can now go into the details of each individual group. It should be noted that we will mainly refer to the countries that have the highest load factors in each group. Countries with low loadings might be a case for further research but given the nature of factor models and the low quality of data, it is obviously not surprising that individual cases with low loadings may not be a perfect fit.

Cluster per cluster analysis

The Classics

The “Classics” are the largest group (containing around 40 per cent of the sample) and closely resemble what much of the public discourse would refer to as the “standard” case for

[13] Correlation coefficients as well as regressions between the cluster FCIs, the US exchange rate and Oil prices are presented in Annex IV (Results Annex).

developing countries. They have strong correlations with nearly all GMC variables, i.e., exchange rates, interest rates and government bond yields. As soon as monetary conditions in the North start to tighten and the US-Dollar appreciates, these countries run into trouble as short-term speculative capital starts to flee the economy. This leads to a sharp currency depreciation and higher US-Dollar denominated debt burden. Especially the Asian and most Latin American economies fit well into this group, as they have very high loadings, as indicated in Table 4.

G1 - "The Classics"		**G2 - "The Terms of Trade Sensitive"**		**G3 - "The Sovereign Debt Strugglers"**		**G4 - "The Alt-Terms of Trade Sensitive"**		**G5 - "The private debt strugglers"**	
Member	*Loading*	*Member*	*Loading*	*Member*	*Loading*	*Member*	*Loading*	*Member*	*Loading*
Singapore	96.2%	Mali	88.5%	Lebanon	91.9%	Kenya	88.3%	Pakistan	86.1%
Malaysia	91.6%	Niger	83.6%	Zimbabwe	83.4%	Uganda	82.4%	Argentina	85.1%
Hong Kong SAR China	88.4%	Lesotho	81.1%	Haiti	78.0%	Nepal	78.8%	Nicaragua	82.3%
China	83.2%	South Africa	79.8%	Tunisia	69.8%	Rwanda	68.6%	Turkey	70.5%
Thailand	81.7%	Burkina Faso	79.1%	Sudan	66.6%	Burundi	33.6%	Philippines	59.3%
Korea	81.4%	Guinea-Bissau	78.4%	Chad	66.4%			Mozambique	57.7%
Russia	81.4%	Colombia	75.8%	Sierra Leone	59.6%			Bangladesh	53.9%
Ghana	78.9%	Togo	71.4%	Egypt	56.3%			India	52.0%
Mexico	78.7%	Botswana	69.2%	El Salvador	54.7%			Jamaica	49.0%
Peru	78.5%	Chile	63.7%	Uruguay	47.4%				
Brazil	78.2%	Benin	63.4%						
Mongolia	76.5%	Namibia	63.4%						
Ecuador	76.3%	Bolivia	63.3%						
Zambia	75.9%	Tanzania	56.0%						
Ukraine	72.4%	Kyrgyz Republic	53.8%						
Algeria	65.2%	Sri Lanka	51.8%						
Paraguay	64.8%	St. Vincent and the Grenadines	45.0%						
Mauritius	63.9%	Kazakhstan	42.7%						
Ethiopia	63.8%	Angola	42.3%						
Indonesia	63.6%	Vietnam	36.2%						
Democratic Republic of the Congo	60.8%	Liberia	29.9%						
Nigeria	59.4%								
Jordan	59.0%								
Cabo Verde	51.5%								
Guinea	51.3%								
The Gambia	48.3%								
Morocco	44.9%								
Venezuela	37.1%								
Madagascar	28.6%								

Table 4 List of countries by cluster and associated loadings

The FCI of this group most vividly illustrates the Minskian boom-and-bust story. The euphoria of the pre-2007 era, marked by an acceleration of financial innovation and rising commodity prices, led to a sharp improvement of financial conditions in this group. Investors' positive sentiments of the past were largely confirmed by high capital gains and returns in the present, which nourished more risk-taking, higher leverage, and an ever-greater appetite for yields. Prior to 2007, many emerging markets became the target of carry traders, which exploited the interest rate differentials between lower yielding and higher yielding currencies (UNCTAD, 2009). During that time, as interest rates in the US started to rise after 2004, Japanese yen- and Swiss franc-funded carry trade operations were highly popular, targeting, amongst other currencies, the Hungarian forint, the Brazilian real, or the Korean won (ibid.). As the speculative positions piled up, the global imbalances increased due to currency appreciations and higher deficits of the carry trade target countries on the one hand, and currency depreciations and higher surpluses on the other. During the summer of 2008, as the turbulences in US financial markets intensified, carry traders started to rapidly unwind their speculative positions. This sell-off and capital flight accelerated in the aftermath of the collapse of Lehman brothers in September 2008, sending the FCI for this group down the drain. The freefall was reversed right after the G20-summit in London in April 2009, which set up wide-ranging capital support to developing and emerging economies via the IMF.

The FCI of the "classics" continued to improve thereafter, nurtured by a speculative frenzy on commodity prices and – again – a new surge of carry trades (UNCTAD, 2011a). In 2010, the then Brazilian finance minister, Guido Mantega, issued his concerns about the competitiveness of the Brazilian economy, in the face of an ever-appreciating exchange rate. He even went so far as to speak of a "currency war"[14], as current account deficits continued to build up and the productive structure of the economy was increasingly suffocated. The apparent stability of the FCI, induced by higher commodity prices and short-term capital inflows, lasted for a short while, before the Fed taper tantrum in May 2013 and the commodity price slump in the summer of 2014 significantly worsened financial conditions across the group, as many large commodity exporters, such as Russia, Peru, Ecuador, Mongolia, or Algeria suddenly saw their foreign reserve revenues evaporate. The downturn was, over time, exacerbated by slowing growth and higher uncertainty in China ('China jitters'), which put a drag on net capital flows into emerging markets, and by the renminbi shock of 2015, reaching a low point in early 2016. Thereafter, financial conditions started to improve from mid-2016 on and, on the backdrop of surprisingly

[14] Financial Times, 27.09.2010, „Brazil in 'currency war' alert", available online: https://www.ft.com/content/33ff9624-ca48-11df-a860-00144feab49a

strong macro news from emerging markets, continued to do so in 2017 despite the cautious, yet persistent tightening of the Fed (BIS, 2017). The renewed downturn followed in 2018, as the US-Dollar started to appreciate vis-à-vis developing and emerging market currencies on the back of strong domestic labour market data and prospective tightening of monetary policy (BIS, 2018). Additionally, emerging trade tensions increased uncertainty, so that the sentiments towards developing and emerging markets changed (ibid.). In the aftermath of this shift in market perceptions, it was especially countries with higher inflation rates and higher current account deficits that faced sharp depreciations. Over the course of the year, volatility in financial markets surged to its highest values since 2011, whilst the turbulences in US equities dragged down equity markets in emerging economies, too. On the 4th of January 2019, the Fed announced to lower its pace of tightening, followed by a series of similar accommodative commitments by the European Central Bank (15th January) and the Bank of Japan (23rd January) (BIS, 2019). Towards the end of the year, optimistic prospects for a Brexit-deal and easing trade tensions between the US and China unleashed bullish sentiments, which were, however, abruptly halted by the concerns of the fallout of the Covid-19 pandemic. The Covid-19 pandemic outbreak in the end of February 2020 triggered capital flight from developing and emerging economies that exceeded the outflows during the GFC (UNCTAD, 2020), whilst commodity prices plummeted (BIS, 2020). Previously bullish investors made a U-turn and financial conditions were again only stabilised by large-scale support programmes from the IMF and the G20 Debt Service Suspension Initiative (DSSI), announced in May 2020. Hence, overall, financial conditions over the past 15 years resemble a ride on a roller coaster for the "classics", which rendered investments and development an incredibly challenging task.

The terms of trade sensitive

Following the "Classics", the "terms of trade sensitive" are the second largest group, as about 30 per cent of the sample fall into this cluster. Together with group 1, therefore, both groups account for about 70 per cent of the sample – which is why we consider both as the "main" group categories of which the other groups are different variants. A defining feature of the "terms of trade sensitive" is that a large share of LICs, i.e., 9 out of 22 economies, are in this group. It equally contains the highest number of African countries, which have particularly high loadings, as indicated in Table 4. Contrary to the "Classics", the "terms of trade sensitive" have significantly lower productive capacities with a very high dependence on subsistence agriculture and exports of raw materials, in many cases even a single commodity. Capital inflows are often FDI for the extraction of resources in the mining sector.

The "terms of trade sensitive" overall benefit from a strong US-Dollar via an improvement of the terms of trade. Moreover, as crude and refined petroleum are the top importing good for countries with the highest loadings in this group, such as South Africa, Mali, or Burkina Faso, the cluster as a whole benefits from lower oil prices.

Above features thus explain some of the diverging trends between the "terms of trade sensitive" and the "classics". While the former was equally hit hard by the GFC, albeit with a higher time lag than the latter, the price surge of some commodities, such as diamonds and, partly, gold, improved financial conditions after 2010. Yet, as the transmission of global economic shocks to domestic markets is low for most economies in this group, due to weak productive structures and low vulnerability to an appreciation of the US-Dollar, the "terms of trade sensitive" remained largely insulated from the vagaries caused by the trade tensions or the prospects for tightening of monetary policy in the US. From 2010 until 2014, the FCI of this group remained stable and improved as the commodity price slump of 2014 lowered the overall energy import bill. Subsequently, as energy prices recovered from early 2016 on, the FCI returned to its pre-commodity price slump level and remained there since. The emerging market sell-off of early 2018, caused by an appreciation of the US-Dollar, the trade tension, the debt crises in Argentina and Turkey, as well as the Covid-19 fallout had almost no impact on financial conditions, as figure 9 well indicates.

The sovereign debt strugglers

The "sovereign debt strugglers" have, as their distinct feature, a very high share public debt to GDP and high debt service to government revenue ratios. Figures 10 and 11 show the respective figures in relation to the other groups, highlighting the distinctiveness of "sovereign debt strugglers" in their debt structure. On the other hand, as private debt plays a comparatively little role in these economies, this group is not as exposed to the booms and busts of private capital flows. As a consequence, its FCI is the most stable one over time in this sample.

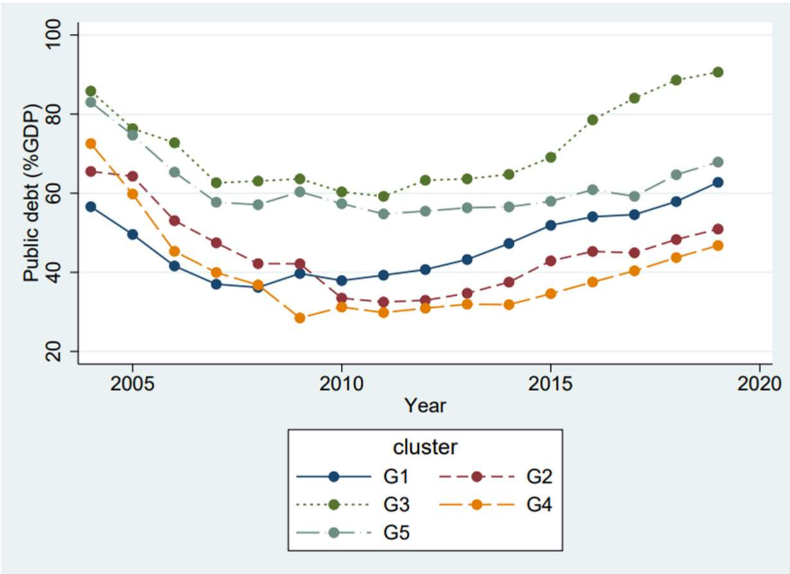

Figure 10 Public debt as a share of GDP (%)
Source: IMF GDD database (Mbaye et al., 2018)

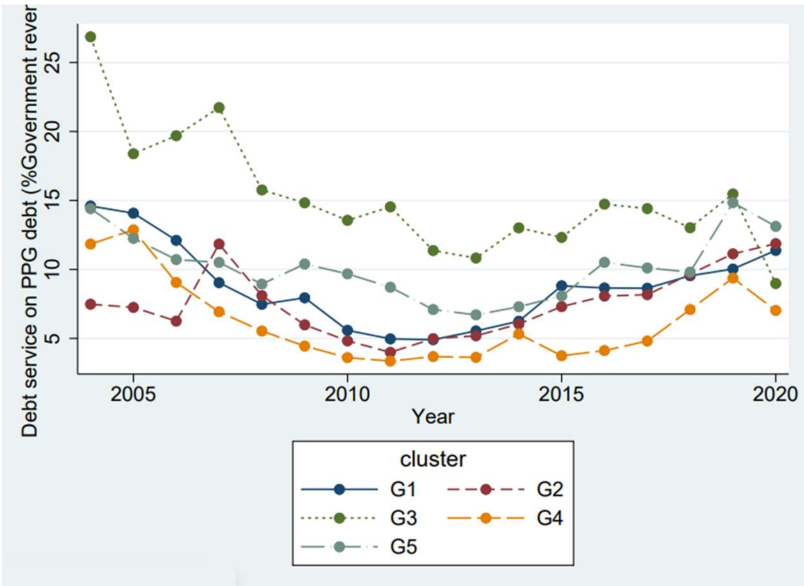

Figure 11 Debt service on PPG debt as a share of government revenues
Source: WDI Indicators and IMF WEO (IMF, 2021)

The borrowing occurs mainly locally, as economies with high loadings in this group, such as Zimbabwe for example, are shut out of international capital markets or have merely "underdeveloped" domestic financial markets. In other cases, we find that this cluster contains countries with disproportionally high shares of remittance inflows that support private consumption. El Salvador (fully dollarised economy) and Haiti are two cases in point, as both have one of the highest shares of remittances to GDP in the world (EIU, 2021a). Egypt, as the world's fifth largest recipient of migrant remittances also fits this pattern, as do Lebanon, Tunisia, and Sudan, where remittances constitute a significant part of foreign exchange inflows in the current account of the balance of payment (World Bank, 2020). This form of foreign exchange inflows does not lead to an accumulation of liabilities vis-à-vis foreign financial actors that come with reimbursement obligations, but they do increase the dependence of the economy on developed economies' performance that is a crucial determinant of migrant remittances to their countries of origin. Moreover, although these inflows reduce the current account deficit, they do not contribute to the diversification of the domestic productive structure and, consequently, structural change. Moreover, even with the remittance inflows, as Figure 12 shows, the "sovereign debt strugglers" stand out vis-à-vis the other clusters with the highest current account deficits.

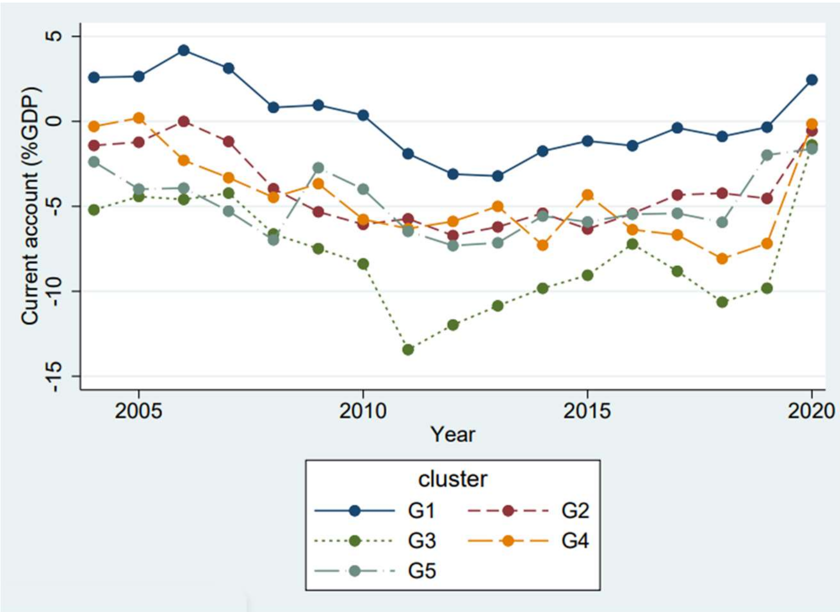

Figure 12 Current account as share of GDP
Source: WDI Indicators

Another commonality across countries in this cluster is that they have an equally low level of productive capacities as the "terms of trade sensitive". Many economies here also rely on subsistence farming and the export of often one single commodity and have been battered by conflicts, violence, disasters, and political instability. Countries such as Haiti, Chad, Zimbabwe, Lebanon, Sudan, Egypt, and Tunisia are unfortunately sad examples of this.

The detachment of the local economy from the vagaries of international capital led to a very stable FCI. The GFC had little impact on financial conditions, neither did the speculation-induced volatility of commodities or the Fed taper tantrum. The FCI started to deteriorate long before the Covid-19 crisis hit, in mid-2016, as many economies started to default on their high public debt burdens, surrendering to a series of recurrent currency crises since 2012. Figure 13 shows that these countries have historically defaulted on larger portions of their sovereign debt. Paradoxically, as the FCI shows, financial conditions in this cluster have been improving during the onset of the pandemic due, mainly, to the G20 Debt Service Suspension Initiative. Yet, this initiative only provided temporary debt relief and finished in December 2021. This means that it is insufficient to allow a sustainable recovery.

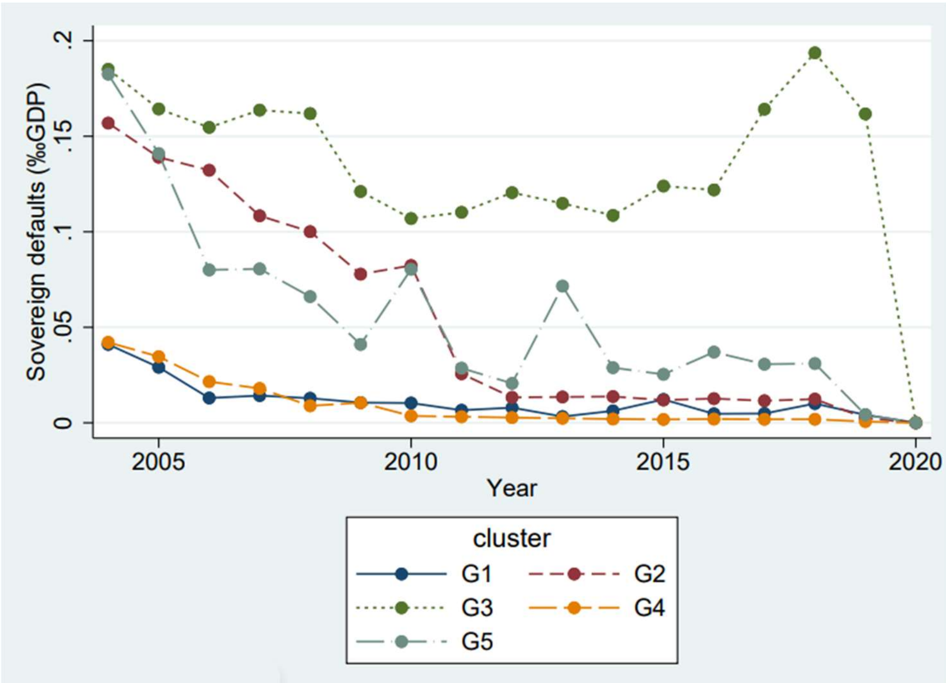

Figure 13 Sovereign defaults as a share of GDP
Source: BoC-BoE Sovereign Default Database (Beers et al., 2020) and WDI Indicators

Thus, despite having the most stable financial conditions in the sample, it is obvious that this group is, similar to the "terms of trade sensitive", in desperate need of structural transformation to mobilise domestic resources in the battle against public debt distress. It also shows that while stable financing conditions are a necessary prerequisite for development, they are, on their own, not sufficient. We will further address this point in the policy recommendations.

The alt-terms of trade sensitive

The "alt-terms of trade sensitive" are the smallest of all groups. Merely five small countries fall into this cluster. It shares the same overall patterns with group 2, what we referred to as the (regular) "terms of trade sensitive", but we do have to stress some of the 'alternative' features of this group. The countries in this group have remarkably synchronised financial conditions and are, in one way or another, sensitive to precious metals, in particular gold. Another distinct feature of this group is that it has, by far and large, the lowest productive capacities in the sample. Economies in this cluster are heavily dependent on subsistence agriculture as well as grants and donations. Figure 14 notably illustrates this by showing the share of ODA in GDP, where the "alt-terms of trade sensitive" remain way ahead of the other clusters.

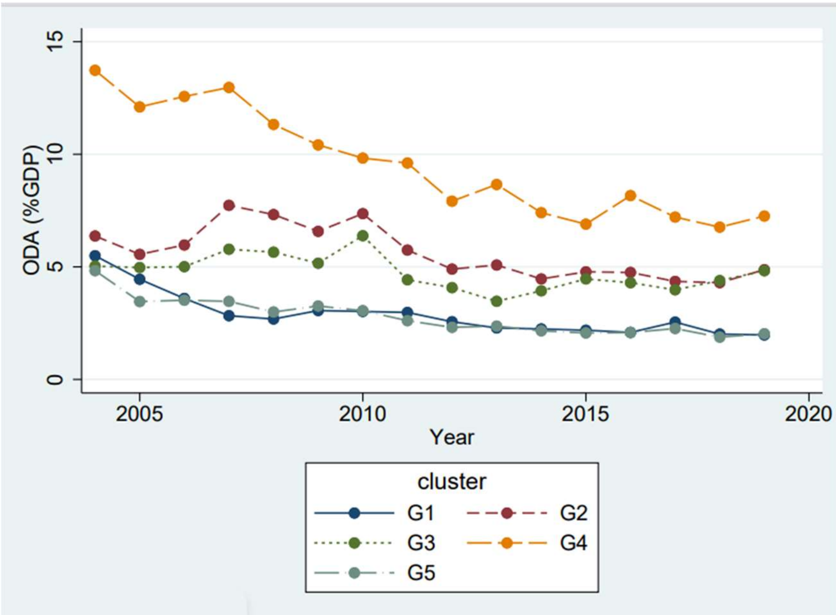

Figure 14 Official Development Assistance as a share of GDP
Source: WDI Indicators

A key characteristic of the evolution of the FCI lies in its geographical location. All "alt-terms of trade sensitive" economies find themselves located in gold trade routes, which connect gold producing areas with gold trading hubs. For most economies, the latter serve as the main export destination. In 2019, for example, 50 per cent[15] of exports from Burundi were destined to the U.A.E. (with gold accounting for almost half of total exports), where also almost 60 per cent of all Ugandan exports ended up (gold making up 57 per cent of total exports here). In the case of

[15] Data from OEC, referring to the year 2019.

Rwanda, close to 30 per cent of total exports were destined to DRC and 35 per cent to the U.A.E (gold amounted to around a third of total exports). Notwithstanding the sensitivity of financial conditions in this cluster to the price of gold, this relationship waned over time and the FCI converged with that of group 2.

The FCI remained generally relatively stable over time, with one noticeable peak in the early 2010s, where the sharp increase is due to the surge in gold prices that were breaking record highs during that time. From late 2012 on, however, gold prices were on the retreat, concomitantly financial conditions rapidly deteriorated. As in the case of group 2, the insulation of international capital markets left financial conditions untouched during the Fed taper tantrum, trade tensions between the US and China, the emerging market sell-off of 2018 or the Covid-19 shock.

The private debt strugglers

The "private debt strugglers" have an extremely volatile FCI as they are exposed, even more so than the "Classics", to the vagaries of international financial markets. Argentina and Turkey have very high loadings in this group, and they are perhaps the most prominent victims of international speculation, high foreign indebtedness, and recurring sovereign debt defaults.

As in case of the "classics", carry trades and short-term speculative portfolio flows lie at the heart of the emerging imbalances in the external sector, as they put upward pressure on the exchange rate. In a stark difference to the "classics", however, the stock of reserves is extremely low in this cluster. Figure 15 shows this in comparison to the other groups. The "private debt strugglers" fall far behind the "classics" and the "sovereign debt strugglers". In relation to GDP, they have only little more reserves in stock than the "alt-terms of trade sensitive", who, as we have seen, have significantly lower productive capacities. This low stock of reserves severely limits the state's capacity to contain a fallout on the exchange rate once the tide turns and capital flees the economy.

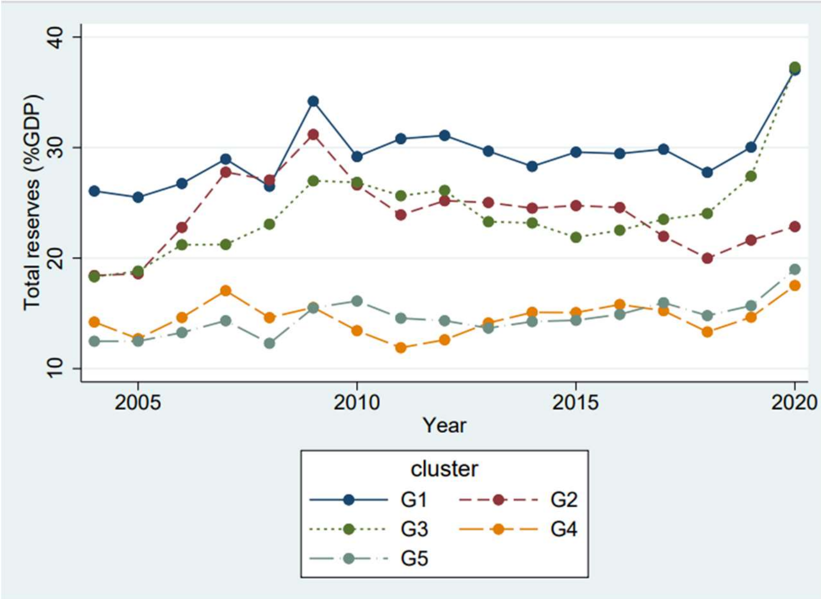

Figure 15 Total Reserves as a share of GDP
Source: WDI Indicators

Another problem is the still very high dollarisation of the "private debt strugglers", even though there has been some improvement compared to the early 2000s. Due to extant levels of dollarisation, however, the stability for individual economies depends on the external finance conditions. Nicaragua, for example, which is a highly dollarised economy with 74 per cent of deposits and 89 per cent of credit denominated in US-Dollar[16], benefits from concessional interest rates and long-term maturity rates (EIU, 2021b). Pakistan too retains reasonable access to international financing, most notably IMF support, and, recently, access to oil facilities with Saudi Arabia worth USD 3.2 billion, which provides valuable balance of payment support (EIU, 2021c). Other economies, such as Argentina and Turkey, on the other hand, have been making headlines by their inability to serve the US-Dollar denominated debt as soon as market sentiments changed, and exchange rates went into freefall.

The case of Turkey is currently the most dramatic example of how a "private debt strugglers" economy can struggle to deal with capital flight and a currency sell-off. About half of total resident deposits are denominated in a foreign currency, mostly in US-Dollars (EIU, 2021d). Moreover, especially before the external value of the lira collapsed in 2018, the private sector heavily borrowed in FX markets and piled up a large stock of foreign currency denominated debt. In the first quarter of 2018, total private sector external debt of financial and non-financial corporations reached a new high of USD 315 billion, which was about 40 per cent of GDP

[16] https://www.fitchratings.com/research/sovereigns/fitch-revises-nicaragua-outlook-to-stable-affirms-idr-at-b-22-11-2019

(ibid.). As market sentiments turned against emerging economies in 2018 and the Turkish lira started to depreciate, accumulated exchange rate risks mercilessly exposed the vulnerabilities of the economy. With a limited stock of reserves and without support from other major central banks, the options to halt the exodus and stabilise the value of the lira were extremely constrained. Large currency mismatches continued to persist as the preferences for holding foreign currency denominated deposits moved at par with the external value of the lira. As the collapse set in in 2018-2019 and financial conditions deteriorated, the preference in the private sector for holding foreign currency deposits increased. As the lira stabilised in 2019, domestic savers were trying to benefit from the weakness of their domestic currency by selling foreign currency denominated deposits. In 2020, however, as the collapse of the lira took off again, the preferences reversed, and savers tried to hang onto their foreign currency deposits again (ibid.).

The key characteristics of the “private debt strugglers” – that is the high private foreign currency denominated debt and the low stock of reserves – explain the much larger volatility of the FCI compared to that of the “Classics” especially in times of actual or anticipated appreciation of the US-Dollar. The taper tantrum in May 2013 is a case in point, as is the market sell-off that shook financial sectors of emerging economies in early 2018. The latter ultimately led to debt crises in Argentina and Turkey that year.

On the other hand, when markets were in a bullish mood and the US-Dollar depreciated, market participants went fully ‘risk-on’. Carry trade speculations took off again, and the concomitant currency appreciation of emerging economies and narrowing of sovereign spreads gave a false sense of security and stability. While foreign currency denominated debt piled up, policymakers and analyst interpreted large-scale capital inflows as signs of confidence, growth, and a bright future outlook. The year of 2017 was marked by such euphoria, as also evident in the FCI of the “private debt strugglers”. Public actors too took advantage of the bullish sentiments. Argentina, for example, used the favourable market conditions to issue a 100-year US dollar-denominated bond yielding 8 per cent in 2017 (BIS, 2017). After the downturn the following year, euphoria was back in 2019, as the US-Dollar weakened, and sovereign yields and spreads approached pre-GFC levels. Bullish sentiments radically changed as the Covid-19 pandemic spread across the world, yet decisive interventions by policymakers and central banks in the global North led to a V-shaped recovery on financial markets. Real yields dived into negative territory in advanced countries, so that equity and bond markets in emerging economies became a viable alternative for yield-starving investors. This has improved financial conditions of the “classics”, as we have seen, and of the “private debt strugglers” – at the price of building up systemic fragilities through high foreign currency denominated debt and volatility of capital flows. Recently, we observed a sharp reversal of capital flows in emerging markets, indicating a continuation of the boom-and-bust patterns that have proven so damaging to stable, long-term, and sustainable development. Addressing the issue and providing overall more stability requires a rethinking of the global monetary system. Additionally, we can provide specific measures for each cluster.

Section VI – Policy recommendation and conclusion

Global policy recommendations

From a Minskian perspective, booms and busts are an integral part of financial capitalism in a fundamentally uncertain world. The ride on the roller coaster for developing and emerging economies is a vivid proof of that. Sustainable development, however, would require stable financing conditions that would enable investment dynamics to kick in and lead to structural transformation. As stable financing conditions are a necessary, yet not sufficient condition for development (as we have seen, for example, in the case of the "sovereign debt strugglers"), it follows that a renewal of productive structures and capacities remains difficult for developing and emerging economies if external financing terms continue to resemble a roller coaster ride – as they have over the past 15 years. To achieve more stability, Minsky (1986) argues that rules need to be simple. One cannot fight a complex system with more complexity, as financial innovation will always outpace regulatory capacities. It is for that reason that we propose a very simple, yet effective set of rules to stabilise financial markets and set up conditions which are accommodative to sustainable and long-term development.

Due to the on-going chaos in foreign exchange markets, meant to be transitory after the collapse of Bretton Woods, the global economy remains in desperate need of a reform of the monetary and financial system that restores stability. Such reforms ought to address at least three policy domains: First, the goal must be to curb speculative capital flows. This can be achieved either via (1) outright capital controls, (2) financial transaction taxes that render short-term currency speculation unprofitable, and (3) restrictions to derivatives trading to those actors that possess the underlying assets. Secondly, to ensure smooth functioning of international trade and development, mechanisms must be put in place that stabilise real exchange rates. To that end, central banks must commit to foreign exchange market interventions to offset inflation rate differentials between different currency areas, which would reduce incentives for carry trades. Third, developing and emerging economies must be granted better, stable, and cheap access to reserve currencies, which would require a reform of multilateral lending practices. This wider access to foreign reserves should go hand in hand with a coordinated increase in global demand to clamp down persistent global imbalances and restore inclusive and sustainable growth paths for all. Last, as debt distress is bound to persist, it is urgent to adopt a new international framework for debt resolution which extends the scope of not only beneficiaries but also creditors. In this regard, as UNCTAD (2020) proposed, an "International Developing Country

Debt Authority" could be established to oversee the implementation of comprehensive temporary standstills as well as case-by-case longer-term debt sustainability assessments and consequent sovereign debt relief and restructuring agreements.

Targeted policy recommendations per cluster

As desirable and necessary as such global institutional adjustments are, the international community has not made significant steps into the right direction over the past 50 years. It had to take tragedies, such as the GFC and the Covid-19 pandemic, with huge socioeconomic toll to see encouraging, yet insufficient, progress. The disappointing experiences do not make it likely that such bold institutional engineering will take place in the near-term future. However, since our FCIs highlights group-specific financial vulnerabilities, it is possible to derive policy recommendations for each individual cluster whose implementation is more within reach in the short term.

For the "Classics", which are vulnerable to global monetary and financial conditions and commodity price shocks, we recommend the implementation of capital controls to insulate the economy from the vagaries of international finance. If capital controls were not a feasible option, for example due to conditionality of external creditors, central banks in emerging and developing economies ought to intervene in foreign exchange markets by offsetting currency appreciations through purchases of foreign exchange reserves (Bofinger, 2011). Additionally, we recommend setting up swap lines and credit facilities with the main currency areas' central banks. In case of high demand for foreign reserves, this would constitute an additional safety buffer to stabilise exchange rates that developing countries could draw on. To address the dependence on and volatility of commodity prices, we propose to set up an international buffer stocks for all main commodities, as proposed by Kaldor (1976). Financing of these stocks should be linked ideally to SDRs. This would prevent sharp appreciations of the US-Dollar and/or a depletion of foreign reserves in times of higher demand for drawing on that stock. It is likely that the very existence of such reserve stocks – in combination with curbs on speculative finance – would suffice to provide commodity price stability and enhance development prospects.

The benefits of more stable commodity prices would also play out in favour of both the "terms of trade sensitive" and "the alt-terms of trade sensitive". Yet, in contrast to the "Classics", much more policy emphasis must be put on diversifying the economy. Their productive capacities lie, on average, below those of group 1 and the dependence on individual commodities, predominantly base and precious metals, tends to be higher. To obtain more stability in capital markets and to let developing countries grow in a sustainable manner, both groups must therefore be granted the policy space to improve regional integration and pursue industrial policy to diversify the economy. In addition to fairer trade and investment agreements, access to cheap and stable funding is required. In this regard, it is crucial that developed economies meet their commitments in terms of ODA and expand availability for concessional finance flows, especially in the constrained context of climate challenge and "just transitions".

The third cluster, the "sovereign debt strugglers" had the most stable financial conditions over time due to higher shares of public as opposed to private external debt. Policy priorities for this group include the expansion of debt relief and debt restructuring programmes to ease the public debt burden, not only in scale but also in scope, i.e., via including developing countries in need, regardless of their GDP per capita. A sufficiently large "breathing space" is required to clamp down recurring sovereign defaults and social unrest. Moreover, to tackle the high and persistent current account deficits, policymakers must stabilise the external sector. The main objective thereby must be boosting exports and speeding-up structural transformation. As in the case of the "terms of trade sensitives", industrial policy, regional integration and increased access to concessional finance are *sine qua non* to this end.

For the fifth cluster, the "private debt strugglers", similar measures as for the "classics" must be put in place. Notably, these economies should adopt capital controls to mitigate the fallout from the boom-and-bust cycles that foreign speculative capital engenders, implement measures to limit excessive leverage in the corporate sector and revive the "profit-investment" nexus to shift private investment towards productive purposes. Given their low stocks of foreign reserves, credit facilities and swap lines, in particular with the Fed, would be a meaningful and effective tool to counter the sharp depreciations these economies recurringly face. In the long run, a de-dollarisation of the economy must become a top priority.

Conclusion

In this paper, we have presented a conceptual and methodological innovation to measure, analyse, and interpret financial conditions in developing and emerging economies. This approach allows for deriving both global reforms of the monetary system and targeted policy measures per cluster, which are based on a comprehensive theory as well as rigorous empirical research. The urgency with which these reforms ought to be addressed can hardly be understated, as stable financing conditions for development will be – after the economic fallout of the Covid-19 pandemic – more important than ever if the global community takes its pledges seriously. In this sense, we look forward to future collaboration with policymakers and academics to work on stabilising unstable capital markets and to further improve our framework presented in this paper.

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Annex

Annex I (Conceptual framework annex)

Capital in neoclassical theory: conceptual confusion

The argument in favour of capital flows liberalisation in developing and emerging economies is mainly grounded in neoclassical theory. Developing and emerging economies are supposed to benefit from adopting such market-friendly reform. According to neoclassical theory, which assumes that individual preferences and methods of production are given in any point of time, market liberalisation leads to a more efficient allocation of scarce resources and therefore better development prospects. The adjustment processes, executed by representative agents optimising their production based on the relative prices of labour and capital, push the economy towards equilibrium, in which the production intensity of each input factor corresponds to its marginal product.

Hence, in neoclassical theory, capital flows are always tied to 'real' economic conditions. In an international economy where countries differ in terms of factor endowments, the liberalisation of trade and finance is a beneficial policy, as aggregate output increases through a more efficient resource allocation across economies. Developing countries would thereby benefit from capital inflows, as the initial scarcity of capital implies higher marginal returns, so that investors would take advantage of the arbitrage opportunity. This leads to an increased allocation of capital from developed countries, where capital is abundant, to developing economies. Therefore, it is through the liberalisation of the financial account that developing economies can obtain the funds needed for investments and the growth of their capital stock, which – following neoclassical growth theory – is a prerequisite for development as it increases productivity and generates higher per capita output. Moreover, as the inflow of capital is assumed to lower the cost of capital in developing countries, it should stimulate further investments until the marginal product of capital equals its marginal costs.

This framework of neoclassical theory does not leave any room for the most pressing challenges and empirical realities that developing countries had to face over the past 50 years. Short-term monetary shocks as well as false pricing in FX and commodity markets, nurtured by frenetic speculation and recurring market frenzy, were an integral feature of global finance and threw developing countries regularly off track. Yet, neoclassical theory – relying on rationalist assumptions – offers no explanation for these phenomena. On a more fundamental level though, neoclassical theory is not only unable to capture the inherent irrationalities of financial markets, but it also fails to adequately conceptualise 'capital' – as it was already outlined in the main part of the paper. During the Cambridge Capital Controversy, the British Keynesian economists proved the impossibility of aggregating a heterogenous set of capital goods into a single 'capital' input factor (Sraffa, 1960). Additionally, they criticised their neoclassical colleagues for their vague and arbitrary use of the concept of 'capital' (Robinson, 1954). At times, neoclassical economists refer to capital as a set of physical goods (i.e., a stock of machinery, buildings, and other means of production). Other times, they prefer to define it as financial resources. Ohlin (1935) and Mundell (1957) – two foundational texts of neoclassical macroeconomic theory – are primary examples of the confusion of orthodox economists with the concept of capital. Alternating between its conceptualisation as 'a sum of money' (Ohlin, 1935, p. 76), on the one hand, and as 'abstract capital' (p. 77) in its physical form on the other, shows this severe conceptual inconsistency. The same applies to Mundell (1957), who was the first to relax the factor immobility assumption in neoclassical trade models, but who was unable to distinguish between portfolio flows and foreign direct investments (FDI). Neoclassical economists thus end up conceptualising capital as an all-purpose good that they employ in whatever way they see fit – regardless of how farfetched and unrealistic such an approach may be.

A capital market is not a conventional market

In addition to the international dimension of trade and capital flows, neoclassical economists and mathematicians developed various models to understand the pricing mechanisms in capital markets, such as markets for equities, bonds and so on. These asset pricing models, regardless of their specific form, i.e., whether we refer to the efficient market hypothesis (EMH), modern portfolio theory (MPT), the capital asset pricing model (CAPM), or arbitrage pricing theory (APT), are essentially discounted future cash flow models underpinned by general equilibrium theory. The key question thereby is always which discount factor is being employed. Conventionally, economists use the interest rate, which is either set as some risk-free rate in the finance literature or, following neoclassical economic theory, determined by the supply and demand of funds in financial markets.

The loanable funds theory, which underpins asset pricing techniques based on popular dynamic stochastic general equilibrium (DSGE) modelling, conceptualises money capital as any other good whose price – the interest rate – is determined by the law of supply-and-demand in financial markets. The supply of these loanable funds are the savings in the economy, the demand for it comes from desired investments (Mankiw, 2013). A higher amount of savings will increase the supply of funds and therefore push down the interest rate, which will subsequently spur investment activity in the economy. Higher investments, on the other hand, reduce the amount of loanable funds, pushing interest rates up again. Banks and other financial institutions function as intermediaries in this framework, in which, as in any other market, the law of supply and demand eventually equilibrates savings and investments. At the equilibrium interest rate, "households' desire to save balances firms' desire to invest, and the quantity of loanable funds supplied equals the quantity demanded" (ibid., p. 69). The preferences for savings and investments themselves are determined by 'real' economic factors, such as demographics for example. Although there exists a range of different versions of loanable funds theory, including some that propose a framework of money creation through credit, the core of above principles remains intact: any credit expansion by private banks increases savings and adds to the supply of loanable funds. This, in turn, lowers the interest rate and thus increases the demand for investments, until the supply and demand of loanable funds is in equilibrium (Bibow, 2001).

There are several flaws with conceptualising the capital market as any other goods market, which is governed by the equilibrating forces of demand and supply. The first problem is that it assumes a given stock of savings, which is a prerequisite for investments. Schumpeter (1912) outright rejected such an assumption as inaccurate more than one hundred years ago, as savings are and always were the outcome of prior investments. Major central banks, including the Bank of England and the Bundesbank, recently confirmed the Schumpeterian point of view (McLeay et al., 2014; Bundesbank, 2017). The second problem is that loanable funds theory argues that all savings turn automatically into investments, so that a higher amount of savings does not adversely affect economic output, but, to the contrary, leads to economic growth. As Keynes (1930) already noted, this does not make any sense. More savings simply reduce corporate profits by the same amount, as one agent's decision not to spend implies forgone income for the counterparty. Whilst additional savings add to the supply of loanable funds, the reduction of profits means that firms require additional funding to finance their investments, so that the demand for loanable funds increases *at par* with the increase in savings. As a consequence, the interest rate does not fall, hence no additional investment is realised. On the other hand, taking a step back from the loanable funds logic, it is even questionable as to what extent firms would commit to the same amount of investments, if savings increased. Considering that businesses operate under fundamental uncertainty (Minsky, 1986), falling demand and lower corporate profits are more likely to lead to firms revising downwards their outlook and adjusting their output accordingly. Higher savings would thus lead to lower investments and national income, hence also lower savings in the long run.

FCIs require a new conceptual approach

Despite the logical consistency of the loanable funds framework, its theory of money, savings, investments, and interest rates, were outright rejected by central banks, as already mentioned, as well as an increasing body of academic literature (cf. McLeay et al., 2014; Bundesbank, 2017). Most importantly, the interest rate is not a result of self-equilibrating market forces, but it is set by the central bank. The latter adjusts its monetary policy based on wage and investment dynamics in the economy, which, in turn, are determined by wage and fiscal policies. In the case of slack demand – the status quo since the financial crisis – central banks are unable to re-start an investment dynamic without the support of fiscal policy, regardless of how far they push down interest rates. It is clear after almost 15 years at the zero lower bound in advanced economies, putting all the weight on monetary policy is as effective as pushing on a string.

The main point with regards to neoclassical capital market theory, which is relevant to the theoretical framework for FCIs, is that interest rates are endogenously determined and stabilised through constant interventions of a public authority – the central bank. The entire yield and credit curve in the economy thus depend on state action, not market forces. In the case of developing countries, there is of course a lot less scope for intervention due to external constraints, making their financial markets particularly vulnerable and unstable, and rendering the need for appropriate monitoring tools all the more important. Yet, as per a preliminary conclusion, given that it is public policy – as opposed to equilibrating forces of supply and demand – which determine financial market outcomes, it implies that it is utterly off the mark to conceptualise capital markets as conventional markets. Capital markets are *sui generis* in nature, and a comprehensive theoretical framework must take this into account.

Despite distancing itself from the notion of self-equilibrating and smoothly functioning financial market, much of the literature on FCIs does not fully consider such idiosyncrasies in its conceptualisation and theorisation of the indicators. Instead, it often assumes that FCIs help to identify periods of crises or stress which are distinct to periods of 'conventional functioning' of financial markets. Following such benchmark assumptions, "financial stress can be thought of as an interruption to the normal functioning of financial markets" (Hakkio and Keeton, 2009, p. 6) or, alternatively, as "impaired financial mediation" (Balakrishnan et al., 2011, p. 40). Identifying financial stress, according to such theoretical underpinnings, is thus a question of identifying the lead-up periods to such market turmoil and intervene correspondingly and selectively.

Yet, the recurring financial crises of the past 50 years – in particular in developing and emerging economies – suggest that comprehending the nature of finance requires conceptualising the exaggerated up- and downturns of asset prices as integral features of global finance in the era of hyperglobalisation. As a consequence, FCIs should be embedded in a theoretical framework that accounts for the *inherent* instabilities and booms and busts of financial markets. As neoclassical economics does neither provide a coherent conceptualisation of capital, nor a theory to understand capital flows or the basic functioning of capital markets, it requires a radically different approach to contextualise FCIs. A more convincing account, which meets these requirements and proves to be more useful to understand the dynamics in the financial markets of developing and emerging economies, is Minsky's financial instability hypothesis. For this reason, it provides the basis for our analysis.

Annex II (Data Annex)

Table 5 Descriptive statistics of the country variables

Variables	HICs (N=5025)	LICs (N=5293)	MICs (N=6030)	Overall (N=16348)
CPIYOY				
Mean (SD)	550 (11000)	7.26 (7.40)	9.87 (35.5)	173 (6040)
Median [Min, Max]	3.84 [-5.17, 386000]	6.07 [-24.0, 65.2]	5.81 [-7.73, 821]	5.27 [-24.0, 386000]
Missing	575 (11.4%)	748 (14.1%)	325 (5.4%)	1648 (10.1%)
CREDIT				
Mean (SD)	645000 (713000)	131000000 (85100000)	27500 (32900)	20500000 (58000000)
Median [Min, Max]	315000 [5460, 2070000]	113000000 [12700000, 272000000]	10200 [-2050, 117000]	28400 [-2050, 272000000]
Missing	4627 (92.1%)	5095 (96.3%)	5352 (88.8%)	15074 (92.2%)
CREDIT2				
Mean (SD)	-	-	3160 (910)	3160 (910)
Median [Min, Max]	-	-	2760 [1920, 5890]	2760 [1920, 5890]
Missing	5025 (100%)	5293 (100%)	5948 (98.6%)	16266 (99.5%)
DEBSER				
Mean (SD)	13.4 (5.86)	-	8.93 (4.26)	12.3 (5.84)
Median [Min, Max]	12.9 [3.20, 31.5]	-	10.0 [3.00, 20.0]	11.7 [3.00, 31.5]
Missing	4440 (88.4%)	5293 (100%)	5835 (96.8%)	15568 (95.2%)
DEPRAT				
Mean (SD)	5.63 (6.00)	8.26 (4.17)	6.05 (3.38)	6.62 (4.74)
Median [Min, Max]	3.81 [0.0100, 57.9]	7.90 [0.0700, 23.9]	5.76 [0, 19.0]	5.90 [0, 57.9]
Missing	986 (19.6%)	1300 (24.6%)	1420 (23.5%)	3706 (22.7%)
DISCRA				
Mean (SD)	9.52 (8.44)	11.0 (8.72)	14.0 (58.9)	11.8 (38.9)

Variables	HICs (N=5025)	LICs (N=5293)	MICs (N=6030)	Overall (N=16348)
MONAGG				
Mean (SD)	38700000 (122000000)	30400 (49500)	2420000 (14500000)	20000000 (88000000)
Median [Min, Max]	72200 [41.1, 642000000]	3430 [1.60, 279000]	31600 [0.108, 303000000]	35900 [0.108, 642000000]
Missing	931 (18.5%)	4114 (77.7%)	3000 (49.8%)	8045 (49.2%)
MONYOY				
Mean (SD)	12.2 (39.6)	240 (5040)	13.9 (35.0)	77.1 (2670)
Median [Min, Max]	9.45 [-100, 1390]	11.4 [-99.9, 131000]	10.4 [-71.7, 662]	10.3 [-100, 131000]
Missing	881 (17.5%)	1898 (35.9%)	1513 (25.1%)	4292 (26.3%)
NOPERL				
Mean (SD)	3.10 (1.33)	16.3 (13.0)	3.45 (4.04)	4.89 (6.85)
Median [Min, Max]	2.94 [0.750, 11.0]	11.0 [2.66, 53.2]	2.22 [0.710, 25.2]	2.93 [0.710, 53.2]
Missing	3942 (78.4%)	5041 (95.2%)	5378 (89.2%)	14361 (87.8%)
PASECI				
Mean (SD)	-	-	284 (90.3)	284 (90.3)
Median [Min, Max]	-	-	276 [140, 613]	276 [140, 613]
Missing	5025 (100%)	5293 (100%)	5690 (94.4%)	16008 (97.9%)
PortDer_Assets				
Mean (SD)	2790 (7330)	7.65 (36.3)	123 (779)	1250 (5000)
Median [Min, Max]	566 [-30400, 64900]	0 [-191, 374]	1.20 [-4640, 9530]	10.8 [-30400, 64900]
Missing	3700 (73.6%)	4957 (93.7%)	4591 (76.1%)	13248 (81.0%)
PortDer_Liabilities				
Mean (SD)	2490 (7730)	110 (564)	448 (2330)	1260 (5340)

Median [Min, Max]	6.50 [0.250, 33.5]	9.95 [0, 72.5]	6.50 [0.500, 975]	7.58 [0, 975]
Missing	2238 (44.5%)	3364 (63.6%)	2573 (42.7%)	8175 (50.0%)
ELMIP				
Mean (SD)	397 (521)	-	264 (99.4)	363 (457)
Median [Min, Max]	216 [100, 2950]	-	261 [109, 707]	232 [100, 2950]
Missing	2052 (40.8%)	5293 (100%)	5025 (83.3%)	12370 (75.7%)
EMBI				
Mean (SD)	93.4 (33.2)	102 (4.97)	92.3 (31.8)	93.2 (32.0)
Median [Min, Max]	104 [0, 151]	103 [80.7, 111]	102 [0, 139]	103 [0, 151]
Missing	1704 (33.9%)	5038 (95.2%)	2753 (45.7%)	9495 (58.1%)
EMBIBS				
Mean (SD)	458 (319)	328 (275)	265 (240)	357 (296)
Median [Min, Max]	371 [33.4, 1730]	146 [73.4, 1120]	167 [46.0, 1490]	248 [33.4, 1730]
Missing	1807 (36.0%)	4859 (91.8%)	2642 (43.8%)	9308 (56.9%)
EMBISO				
Mean (SD)	-	-	-	-
Median [Min, Max]	-	-	-	-
Missing	5025 (100%)	5293 (100%)	6030 (100%)	16348 (100%)
ESTATI				
Mean (SD)	382000000000 (6610000000000)	-	185 (196)	228000000000 (5100000000000)
Median [Min, Max]	386 [20.7, 180000000000000]	-	100 [3.20, 917]	256 [3.20, 180000000000000]
Missing	2285 (45.5%)	5293 (100%)	4165 (69.1%)	11743 (71.8%)
FINANI				
Mean (SD)	70100000000 (1290000000000)	-	2370 (3470)	42300000000 (1000000000000)
Median [Min, Max]	1280 [34.5, 39300000000000]	-	726 [20.7, 20400]	1080 [20.7, 39300000000000]
Missing	1818 (36.2%)	5293 (100%)	3921 (65.0%)	11032 (67.5%)
FUNDUS				

Median [Min, Max]	574 [-31800, 111000]	0 [-2190, 3660]	1.90 [-16200, 21700]	10.0 [-31800, 111000]
Missing	3708 (73.8%)	4957 (93.7%)	4518 (74.9%)	13183 (80.6%)
PRICOM				
Mean (SD)	74.5 (25.2)	74.5 (25.2)	74.5 (25.2)	74.5 (25.2)
Median [Min, Max]	68.3 [24.9, 141]	68.3 [24.9, 141]	68.3 [24.9, 141]	68.3 [24.9, 141]
Missing	0 (0%)	67 (1.3%)	0 (0%)	67 (0.4%)
PRIMRA				
Mean (SD)	8.23 (3.78)	13.1 (5.73)	12.6 (7.66)	11.6 (6.45)
Median [Min, Max]	7.25 [1.75, 32.6]	11.0 [7.48, 40.8]	10.8 [3.16, 85.0]	10.0 [1.75, 85.0]
Missing	3252 (64.7%)	3053 (57.7%)	3663 (60.7%)	9968 (61.0%)
REER				
Mean (SD)	99.4 (42.2)	92.9 (22.4)	101 (17.1)	99.0 (30.4)
Median [Min, Max]	98.6 [48.8, 1180]	96.7 [18.4, 148]	99.5 [54.5, 191]	98.7 [18.4, 1180]
Missing	944 (18.8%)	3358 (63.4%)	1623 (26.9%)	5925 (36.2%)
RESERV				
Mean (SD)	210 (559)	484 (1590)	1620 (7790)	825 (4900)
Median [Min, Max]	55.4 [1.29, 4060]	0.732 [0, 11300]	17.7 [0.135, 102000]	16.4 [0, 102000]
Missing	514 (10.2%)	708 (13.4%)	587 (9.7%)	1809 (11.1%)
RESMOM				
Mean (SD)	0.740 (6.74)	3.92 (65.4)	1.05 (15.7)	1.78 (36.9)
Median [Min, Max]	0.426 [-39.3, 257]	-0.157 [-82.5, 2810]	0.350 [-70.2, 939]	0.300 [-82.5, 2810]
Missing	711 (14.1%)	1597 (30.2%)	1385 (23.0%)	3693 (22.6%)
RESPRO				
Mean (SD)	109 (25.2)	-	114 (38.4)	110 (29.7)
Median [Min, Max]	102 [49.6, 199]	-	104 [52.1, 338]	102 [49.6, 338]
Missing	4172 (83.0%)	5293 (100%)	5692 (94.4%)	15157 (92.7%)
RESYOY				

Mean (SD)	616 (3990)	455 (1790)	547 (1620)	538 (2600)
Median [Min, Max]	0 [0, 46100]	103 [0, 15000]	22.4 [0, 20300]	15.5 [0, 46100]
Missing	275 (5.5%)	93 (1.8%)	61 (1.0%)	429 (2.6%)
GDP				
Mean (SD)	213 (517)	14600 (71100)	1570000 (8290000)	560000 (4980000)
Median [Min, Max]	79.1 [0.0120, 4470]	2.55 [0.140, 487000]	25.0 [0.231, 67100000]	18.8 [0.0120, 67100000]
Missing	3621 (72.1%)	3667 (69.3%)	4372 (72.5%)	11660 (71.3%)
GOVYLD				
Mean (SD)	6.30 (4.35)	15.0 (2.19)	9.90 (4.98)	8.29 (5.11)
Median [Min, Max]	5.19 [0.424, 63.0]	15.0 [5.42, 19.5]	8.50 [2.07, 38.0]	7.44 [0.424, 63.0]
Missing	2106 (41.9%)	5016 (94.8%)	3568 (59.2%)	10690 (65.4%)
INOVER				
Mean (SD)	6.40 (15.1)	7.40 (7.75)	8.22 (5.01)	7.22 (11.0)
Median [Min, Max]	3.50 [0, 329]	5.34 [0.0200, 92.0]	7.47 [0, 40.0]	5.17 [0, 329]
Missing	1647 (32.8%)	2989 (56.5%)	3703 (61.4%)	8339 (51.0%)
LENRAT				
Mean (SD)	11.6 (9.95)	18.0 (12.0)	17.1 (45.3)	15.7 (28.9)
Median [Min, Max]	8.71 [2.63, 85.6]	16.3 [4.37, 71.0]	12.0 [5.10, 1180]	12.0 [2.63, 1180]
Missing	1294 (25.8%)	1324 (25.0%)	1630 (27.0%)	4248 (26.0%)

Mean (SD)	9.88 (29.1)	42.7 (240)	13.3 (50.9)	20.7 (135)
Median [Min, Max]	5.22 [-56.2, 523]	6.45 [-98.5, 4780]	7.77 [-77.0, 1210]	6.51 [-98.5, 4780]
Missing	722 (14.4%)	1608 (30.4%)	1408 (23.4%)	3738 (22.9%)
STOEXI				
Mean (SD)	22200 (88100)	1600 (4780)	133000 (2500000)	57700 (1510000)
Median [Min, Max]	2980 [0, 1920000]	242 [98.1, 35100]	3760 [63.5, 96800000]	2080 [0, 96800000]
Missing	1185 (23.6%)	3258 (61.6%)	2704 (44.8%)	7147 (43.7%)
TREBIL				
Mean (SD)	4.52 (3.77)	11.0 (7.04)	8.18 (5.18)	6.85 (5.40)
Median [Min, Max]	3.49 [-0.380, 24.7]	9.53 [0.300, 42.2]	7.21 [0.0710, 27.0]	5.75 [-0.380, 42.2]
Missing	2513 (50.0%)	4625 (87.4%)	3752 (62.2%)	10890 (66.6%)
VOLATI				
Mean (SD)	18.0 (13.3)	-	33.3 (19.3)	21.1 (15.9)
Median [Min, Max]	18.2 [0.490, 89.7]	-	26.4 [17.2, 168]	21.9 [0.490, 168]
Missing	4289 (85.4%)	5293 (100%)	5842 (96.9%)	15424 (94.3%)

Variable	*CPIYOY*	*CREDIT*	*CREDIT2*	*DEBSER*	*DEPRAT*	*DISCRA*	*ELMIP*	*EMBI*	*EMBIBS*	*EMBISO*	*ESTATI*	*FINANI*	*FUNDUS*	*GDP*	*GOVYLD*	*INOVER*	*LENRAT*	*MONAGG*	*MONYOY*	*NOPERL*	*PASECI*	*PortDer_Assets*	*PortDer_Liabilities*	*PRICOM*	*PRIMRA*	*REER*	*RESERV*	*RESMOM*	*RESPRO*	*RESYOY*	*STOEXI*	*TREBIL*	*VOLATI*
Algeria	✓	✓			✓	✓		✓					✓				✓							✓		✓	✓	✓		✓	✓		
Angola	✓	✓			✓	✓		✓	✓				✓			✓	✓	✓	✓					✓			✓	✓		✓			
Argentina					✓		✓	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓					✓		✓	✓	✓		✓	✓		
Bangladesh	✓	✓			✓	✓							✓				✓	✓	✓					✓	✓		✓	✓		✓	✓		
Benin	✓				✓								✓			✓	✓		✓					✓	✓		✓	✓		✓	✓		
Bolivia	✓				✓	✓		✓	✓				✓				✓	✓	✓	✓				✓		✓	✓	✓		✓			
Botswana	✓				✓	✓							✓				✓	✓	✓	✓				✓	✓		✓	✓		✓			
Brazil	✓				✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓					✓	✓	✓	✓	✓		✓	✓	✓	✓
Burkina Faso	✓				✓								✓			✓	✓		✓					✓	✓		✓	✓		✓	✓		
Burundi	✓					✓							✓				✓		✓					✓		✓	✓	✓		✓			

Cabo Verde	✓				✓	✓							✓				✓		✓					✓		✓	✓	✓		✓			
Chad	✓				✓	✓							✓						✓	✓				✓			✓	✓		✓			
Chile	✓				✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓	✓				✓		✓	✓	✓		✓	✓	✓	
China	✓				✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓					✓	✓	✓	✓	✓		✓	✓	✓	✓
Hong Kong	✓				✓	✓	✓				✓	✓			✓	✓	✓	✓	✓					✓	✓	✓	✓	✓		✓	✓	✓	✓
Colombia	✓				✓	✓	✓	✓	✓			✓	✓		✓	✓	✓	✓	✓	✓				✓	✓	✓	✓	✓		✓	✓		
Congo	✓				✓	✓							✓							✓				✓									
Cuba													✓											✓									
DR Congo					✓	✓							✓			✓	✓							✓		✓	✓	✓		✓			
Ecuador	✓	✓			✓	✓		✓	✓				✓			✓			✓	✓				✓		✓	✓	✓		✓			
Egypt	✓				✓	✓	✓		✓		✓	✓	✓		✓		✓		✓					✓		✓	✓	✓		✓	✓	✓	

El Salvador	✓								✓				✓						✓	✓				✓		✓	✓	✓		✓			
Ethiopia	✓												✓											✓			✓						
Gambia	✓				✓								✓				✓		✓					✓		✓	✓	✓		✓			
Ghana	✓				✓			✓	✓				✓			✓			✓					✓	✓	✓	✓	✓		✓	✓	✓	
Guinea	✓				✓	✓							✓											✓			✓	✓		✓			
Guinea-Bissau	✓				✓								✓			✓	✓		✓					✓	✓		✓	✓		✓	✓		
Haiti	✓				✓								✓				✓	✓						✓			✓						
India	✓				✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓					✓	✓	✓	✓	✓		✓	✓	✓	
Indonesia	✓				✓		✓	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓					✓		✓	✓	✓		✓	✓	✓	
Iran	✓							✓					✓											✓		✓					✓		
Jamaica	✓							✓	✓				✓				✓		✓					✓			✓	✓		✓			

Jordan	✓					✓		✓	✓		✓	✓	✓			✓	✓		✓					✓	✓		✓	✓		✓	✓		
Kazakhstan	✓							✓	✓				✓			✓		✓	✓					✓		✓	✓	✓		✓	✓		
Kenya	✓				✓								✓		✓	✓	✓	✓	✓					✓	✓		✓	✓		✓	✓	✓	
Korea	✓				✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓					✓		✓	✓	✓		✓	✓	✓	✓
Kyrgyzstan	✓				✓	✓							✓				✓		✓					✓		✓	✓	✓		✓			
Lebanon	✓				✓	✓		✓	✓				✓			✓	✓	✓	✓					✓			✓	✓		✓	✓		
Lesotho	✓				✓	✓							✓				✓		✓					✓	✓	✓	✓	✓		✓			
Liberia	✓				✓								✓				✓		✓					✓			✓	✓		✓			
Madagascar	✓				✓								✓				✓		✓					✓			✓	✓		✓			
Malawi	✓				✓								✓			✓	✓		✓					✓	✓	✓	✓	✓		✓	✓	✓	
Malaysia	✓	✓			✓		✓	✓	✓		✓	✓	✓		✓		✓	✓	✓					✓		✓	✓	✓		✓	✓	✓	

Mali	✓				✓								✓			✓	✓		✓					✓	✓		✓	✓		✓	✓		
Mauritius	✓				✓								✓				✓	✓	✓					✓	✓		✓	✓		✓	✓	✓	
Mexico	✓				✓		✓	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓	✓				✓		✓	✓	✓		✓	✓	✓	✓
Mongolia	✓				✓				✓				✓				✓		✓					✓		✓	✓						
Morocco	✓				✓	✓		✓	✓		✓	✓	✓		✓	✓		✓	✓					✓		✓	✓	✓		✓	✓	✓	
Mozambique	✓	✓			✓	✓							✓				✓	✓	✓					✓	✓	✓	✓	✓		✓		✓	
Namibia	✓				✓			✓					✓				✓		✓					✓	✓	✓	✓	✓		✓	✓		
Nepal	✓					✓							✓			✓		✓						✓			✓						
Nicaragua	✓				✓								✓				✓	✓	✓					✓		✓	✓	✓		✓			
Niger	✓				✓								✓			✓	✓		✓					✓	✓		✓	✓		✓	✓		
Nigeria	✓	✓			✓			✓	✓			✓	✓		✓		✓	✓	✓		✓			✓	✓	✓	✓	✓		✓	✓	✓	

Pakistan	✓				✓	✓		✓	✓			✓	✓		✓			✓	✓					✓		✓	✓	✓		✓		✓	
Paraguay	✓				✓	✓			✓				✓				✓	✓		✓				✓		✓	✓						
Peru	✓				✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	✓		✓					✓		✓	✓	✓		✓	✓	✓	
Philippines	✓				✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓					✓	✓	✓	✓	✓		✓	✓	✓	
Russia	✓				✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓		✓			✓	✓	✓	✓	✓		✓	✓	✓	✓
Rwanda	✓				✓	✓							✓			✓	✓							✓			✓				✓		
Saint Vincent and the Grenadines	✓				✓	✓							✓				✓	✓	✓					✓		✓	✓						
Saudi Arabia	✓							✓			✓	✓	✓					✓	✓					✓		✓	✓	✓		✓	✓		
Sierra Leone	✓				✓								✓				✓		✓					✓	✓	✓	✓	✓		✓			

Singapore	✓				✓		✓				✓	✓	✓		✓	✓	✓	✓	✓					✓	✓	✓	✓	✓		✓	✓	✓	
South Africa	✓				✓		✓	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓	✓				✓	✓	✓	✓	✓		✓	✓	✓	
Sri Lanka					✓	✓					✓	✓	✓			✓	✓		✓					✓	✓	✓	✓	✓		✓	✓	✓	
Sudan	✓												✓						✓					✓									
Tajikistan	✓				✓								✓				✓	✓	✓					✓			✓	✓		✓			
Tanzania	✓				✓	✓		✓					✓		✓	✓	✓	✓	✓					✓	✓		✓	✓		✓	✓		
Thailand	✓				✓	✓	✓	✓			✓	✓	✓		✓	✓	✓	✓						✓	✓	✓	✓	✓		✓	✓	✓	
Togo	✓				✓								✓			✓	✓		✓					✓	✓	✓	✓	✓		✓	✓		
Tunisia	✓							✓	✓		✓		✓		✓			✓	✓					✓		✓	✓	✓		✓	✓		
Turkey	✓				✓	✓	✓	✓	✓		✓	✓	✓		✓	✓		✓	✓					✓		✓	✓	✓		✓	✓	✓	
Uganda	✓				✓	✓							✓		✓		✓	✓	✓					✓	✓	✓	✓	✓		✓	✓	✓	

Ukraine	✓				✓	✓			✓				✓			✓	✓	✓	✓					✓		✓	✓	✓		✓	✓		
Uruguay	✓				✓	✓		✓	✓				✓				✓	✓	✓					✓		✓	✓	✓		✓			
Venezuela	✓				✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓					✓		✓	✓	✓		✓	✓	✓	
Viet Nam	✓				✓	✓		✓	✓		✓	✓	✓		✓	✓	✓							✓	✓	✓	✓				✓	✓	
Yemen					✓								✓				✓							✓			✓						
Zambia	✓				✓	✓		✓	✓				✓		✓		✓	✓						✓	✓	✓	✓				✓	✓	
Zimbabwe	✓												✓				✓	✓	✓					✓	✓		✓	✓		✓			

Table 6 Listing of including variables for each country

Annex III (Methodological Annex)

Stage 1: Precisions for the Estimation of the Nonparametric Time-Varying Model.

We now discuss in more details the estimation of model 5).

In our simulations we conventionally used an Epanechnikov kernel. To select the bandwidth, we used the Silverman's rule of thumb, which gives $\mathrm{h_i} = \left(2.35\sqrt{12}\right)\mathrm{T}^{-1/5}\mathrm{p_i}^{-1/10}$. As in any factor model, the factors are unique up to a sign, which is discuss further in a subsection below. However, the time-varying factor model adds another complexity as this identifiability issue can translate locally. Indeed, for $\mathrm{r} = 1, \dots, \mathrm{T}$, each problem in 7) is unique up to a sign. Therefore, for each r, we may have a different sign. Su & Wang, 2017, recommend setting the sign of the loadings according to the first one, $\hat{\boldsymbol{\lambda}}_{i,1}$, and they point that this is not an issue in simulation studies.

However, in our experience with our data sets, we have seen that the sign of the factors may however flip locally, due to the estimation error. To avoid this issue, we implement an alternative two-step method which makes use of non-negative PCA to obtain the correct time-varying factors. We now describe our ad-hoc two-step approach that is able to overcome these issues.

The algorithm relies on the fact that there are two types of time-varying loadings: those which never cross the zero line, for any time point t, and are either positive or negative, and those which do cross the line once or several times. We assume that there is at least one loading of the former type. The algorithm consists in estimating a rolling PCA where we constrain the time-varying loadings to the same signs as the fixed loadings in the standard PCA problem. This way, each estimated time-varying loading $\lambda_{i,t}$ is restricted to be either positive or negative all along the time points. This allows us to recover a good approximation of the factor while avoiding any sign flipping issue. If the true loading crosses the line, the estimated loading will be 0 at some time points. We will thus re-estimate these loadings through an unrestricted nonparametric regression over the estimated factors. Finally, we will re-estimate the factors again to take into account these updated loadings.

In the first step of the algorithm, we compute the PCA (with fixed coefficients) on the real observations $\mathbf{Y}_{i,t}$. Let's call $\widehat{\boldsymbol{\beta}}_i$ the corresponding estimated loadings. We let $\hat{\mathbf{s}}_i := \mathrm{sign}\left(\widehat{\boldsymbol{\beta}}_i\right)$ and solve the following problem:

$$\min_{\boldsymbol{\gamma}_{i,r}, \{Z_{i,t}\}_{t=1}^{T}} \sum_{t=1}^{T} \| \hat{\mathbf{s}}_i \circ \mathbf{Y}_{i,t}^{(r)} - \boldsymbol{\gamma}_{i,r} F_{i,t}^{(r)} \|_2^2,$$
$$\text{subject to } \boldsymbol{\gamma}_{i,r} \geq 0,$$

10)

where $\circ$ denotes the Hadamard (or element-wise) product. Recall that $\mathbf{Y}_{i,t}^{(r)} := \sqrt{K_h\left(\frac{t-r}{T}\right)}\mathbf{Y}_{i,t}$ and $F_{i,t}^{(r)} := \sqrt{K_h\left(\frac{t-r}{T}\right)} F_{i,t}$. Equation 10) is a non-negative PCA problem and we obtain the estimators $\hat{\boldsymbol{\gamma}}_{i,t}$ following the method in Sigg & Buhmann, 2008. We set $\tilde{\boldsymbol{\lambda}}_{i,t} = \hat{\mathbf{s}}_i \circ \hat{\boldsymbol{\gamma}}_{i,t}$ and we estimate the factors by $\tilde{F}_{t,i} = \tilde{\boldsymbol{\lambda}}_{i,t}^{\top} Y_{i,t} / \left(\tilde{\boldsymbol{\lambda}}_{i,t}^{\top} \tilde{\boldsymbol{\lambda}}_{i,t}\right)$.

In the second step of the algorithm, we re-estimate the loadings according to whether they touch the zero line. If $\tilde{\lambda}_{ir,j} \neq 0$ for any $r = 1, \ldots, T$, we set $\hat{\lambda}_{i,rj} = \tilde{\lambda}_{i,r}$. However, if $\tilde{\lambda}_{i,rj} = 0$ for some r, we replace it by

$$\hat{\lambda}_{i,rj} \in \operatorname{argmin}_{\lambda_{i,rj}} \sum_{t=1}^{T} \left(Y_{i,tj} - \lambda_{i,rj} \hat{F}_{i,t}\right)^2 K\left(\frac{t-r}{T}\right),$$

for $r = 1, \ldots, T$. Finally, we re-estimate the factors by $\hat{Z}_{t,i} = \hat{\boldsymbol{\lambda}}_{i,t}^{\top} Y_{i,t} / \left(\hat{\boldsymbol{\lambda}}_{i,t}^{\top} \hat{\boldsymbol{\lambda}}_{i,t}\right)$.

Stage 2: Precisions for the Estimation of the Automatic Clustering

To estimate model 9) we consider the following constrained least-squares problem:

$$\min_{\{\boldsymbol{\alpha}_i\}_{i=1}^{n}, \{G_t\}_{t=1}^{T}} \frac{1}{\mathrm{nT}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \sum_{\mathrm{t}=1}^{\mathrm{T}} \left(\hat{F}_{i,t} - \boldsymbol{\alpha}_{\mathrm{i}}{}' \mathbf{G}_{\mathrm{t}}\right)^2$$

$$\text{subject to } \|\boldsymbol{\alpha}_i\|_0 = 1, \qquad 11)$$

Problem 11) is complex since both the $\boldsymbol{\alpha}_i$ and $\boldsymbol{G}_t$ are unknown. A typical strategy to solve the problem is through an alternate minimization algorithm. However, while 11) is convex with respect to $\boldsymbol{G}_t$, it is not convex with respect to $\boldsymbol{\alpha}_i$. In particular, it is a typical combinatorial problem and thus hard to solve (for more information on similar problems that use the ℓ_1-norm, see for instance Natarajan, 1995, or Nguyen et al., 2019). However, Candès et al. (2006) and Donoho (2006) have shown that convex relaxation with sufficiently sparse solutions can be used to recover the support in constrained regression. This specifically amounts to solving the same minimization problem where the ℓ_0-norm is replaced by the ℓ_1-norm, which is the best convex approximation to the ℓ_0-norm. In our framework, we therefore propose the following algorithm.

For $k = 1,2, \dots K$, where K is large enough, we repeat the following steps:

1. Given $\widehat{\mathbf{F}}_t^{(k-1)}$, for $i = 1,2, \dots, n$ we estimate $\boldsymbol{\alpha}_i$ using the Lasso problem:

$$\widehat{\boldsymbol{\alpha}}_i^{(k)} \in \operatorname{argmin}_{\boldsymbol{\alpha}_i \in \mathbb{R}^q} \frac{1}{T} \sum_{t=1}^{T} \left(\widehat{F}_{i,t} - \boldsymbol{\alpha}_i^\top \widehat{\mathbf{G}}_t^{(k-1)} \right)^2 + r_k^i \|\boldsymbol{\alpha}_i\|_1$$

   where we let r_k^i be suitable non-decreasing sequences such that $\|\widehat{\boldsymbol{\alpha}}_i^{(K)}\|_0 = 1$ is met.

2. Given $\widehat{\boldsymbol{\alpha}}_i^{(k)}$, we estimate the factors by the standard least-squares solution:

$$\widehat{\mathbf{G}}_t^{(k+1)} = \left(\sum_{i=1}^{n} \widehat{\boldsymbol{\alpha}}_i^{(k)} \, \widehat{\boldsymbol{\alpha}}_i^{(k)\top} \right)^{-1} \sum_{i=1}^{n} \widehat{\boldsymbol{\alpha}}_i^{(k)} \, \widehat{F}_{i,t}.$$

For the starting value, we implement a Principal Component Analysis (PCA) on $\widehat{\boldsymbol{F}}_t$ and we

and we select $\widehat{\mathbf{G}_\mathrm{t}^{(0)}}$ as the first q principal factors.

Finally, to obtain the estimators, we re-estimate $\boldsymbol{\alpha}_i$ by their least squares estimates restricted to the support of $\widehat{\boldsymbol{\alpha}}_i^{(K)}$, that is

$$\widehat{\boldsymbol{\alpha}}_i \in \operatorname{argmin}_{\boldsymbol{\alpha}_i \in \mathbb{R}^q} \frac{1}{T} \sum_{t=1}^{T} \left(\widehat{F}_{i,t} - \sum_{l=1}^{q} \alpha_{i,l} \, \widehat{\mathrm{G}}_{\mathrm{i,t}}^{(\mathrm{K})} \mathbb{1}\left(\widehat{\alpha}_{i,l}^{K} \neq 0\right) \right)^2,$$

and $\widehat{\boldsymbol{G}}_t = \left(\sum_{i=1}^{n} \widehat{\boldsymbol{\alpha}}_i \widehat{\boldsymbol{\alpha}}_i{}'\right)^{-1} \sum_{\mathrm{i}=1}^{\mathrm{n}} \widehat{\boldsymbol{\alpha}}_i^{(k)} \, \widehat{F}_{i,t}$, and where $\mathbb{1}(\cdot)$ is the indicator function that takesk the value 1 if its argument is true, and 0 otherwise. Note that the selection of the sequences r_i^k is essential and

controls the convergence of the algorithm. Empirically, we have seen that selecting $K = 30$ and

taking a linear sequence, i.e. $r_K^i = (k/K) r_K^l$ where r_K^i satisfies $\left\| \widehat{\alpha}_i^{(K)} \right\|_0 = 1$ is effective.

Annex IV (Results Annex)

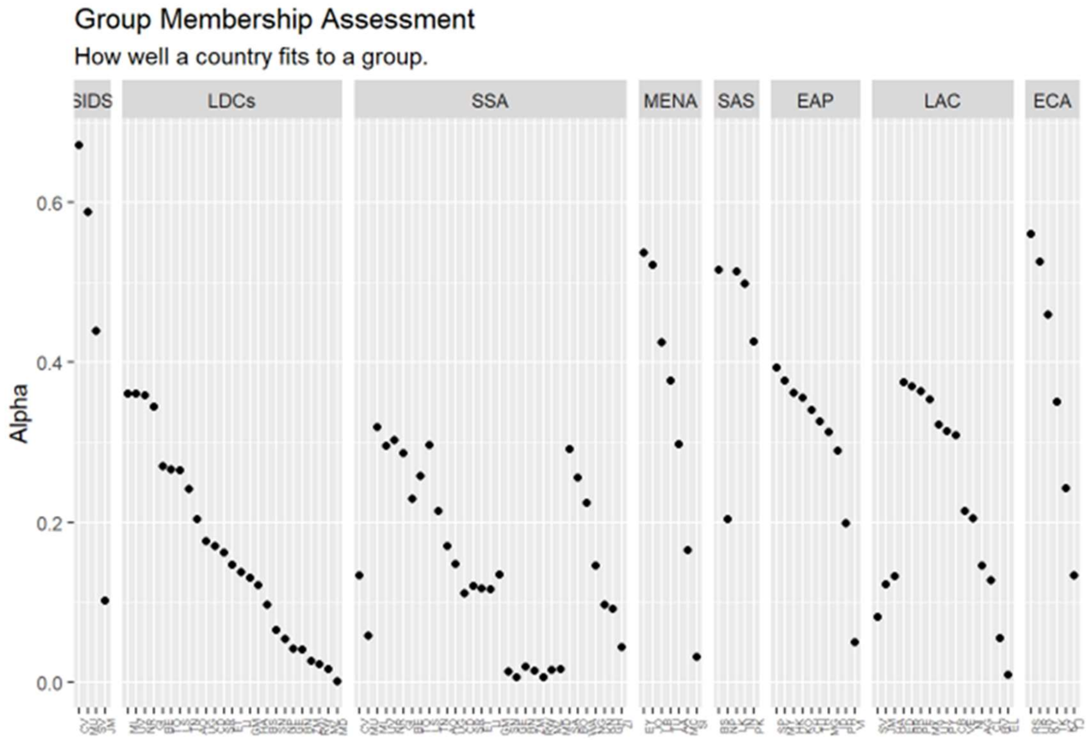
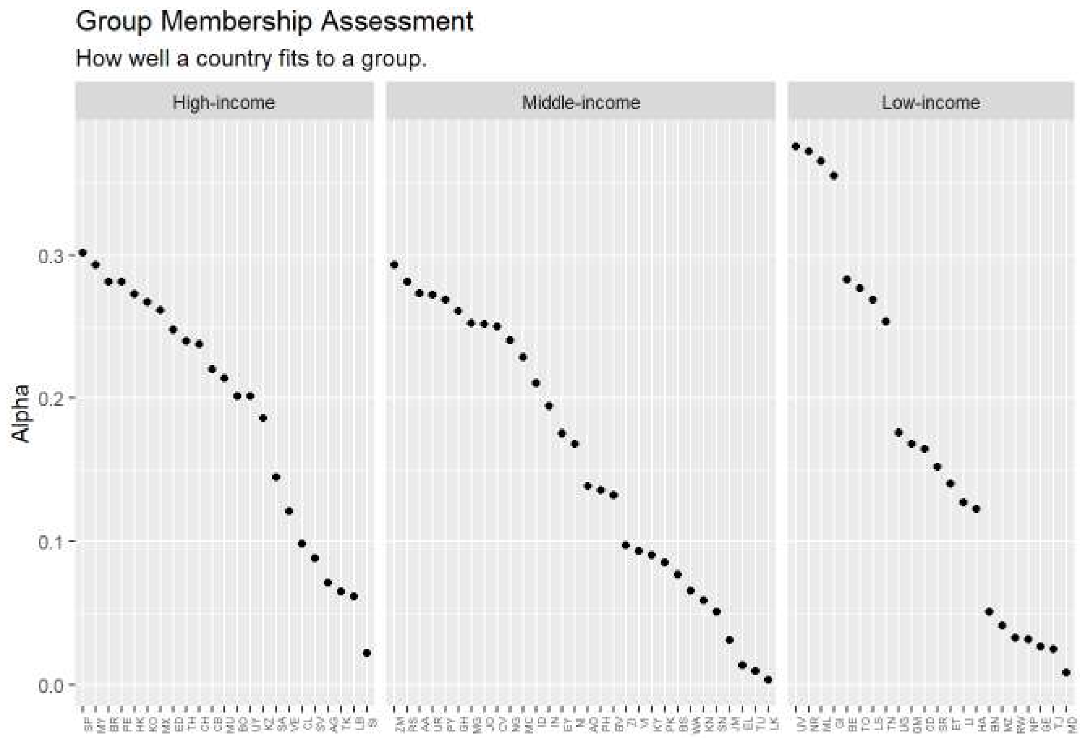


Figure 16 Distribution of loadings for ex-ante income classification



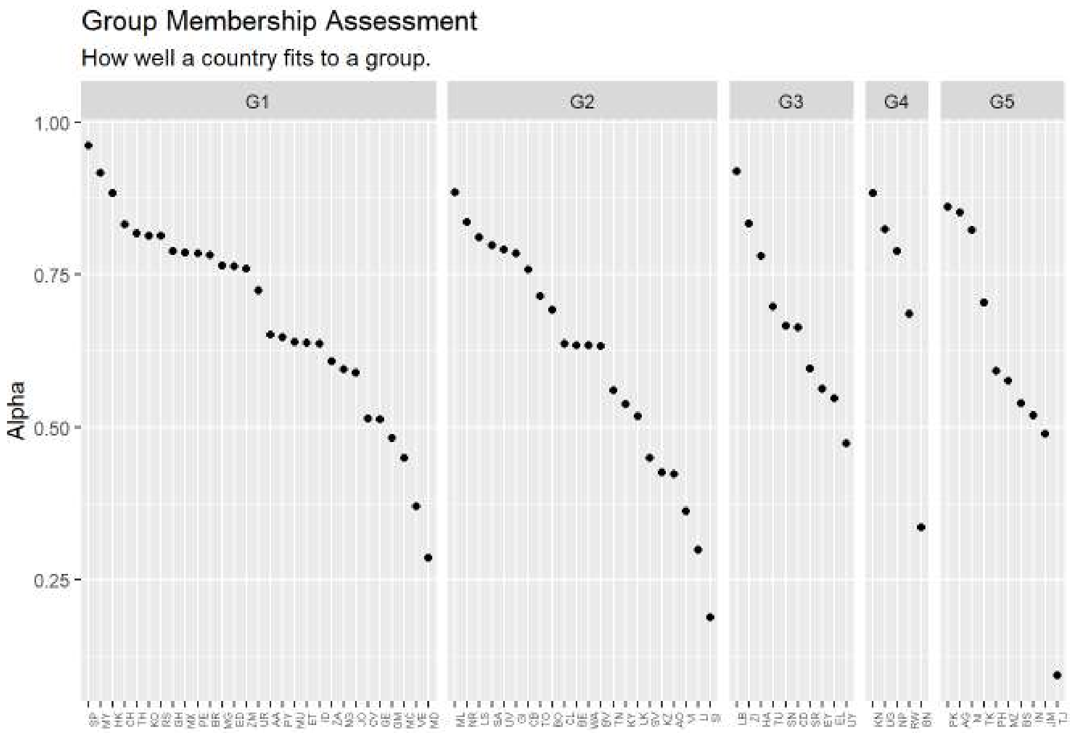


Figure 17 Cluster FCIs for income Classification (fixed loadings)

Figure 18 Cluster FCIs for geographic classification (fixed loadings)

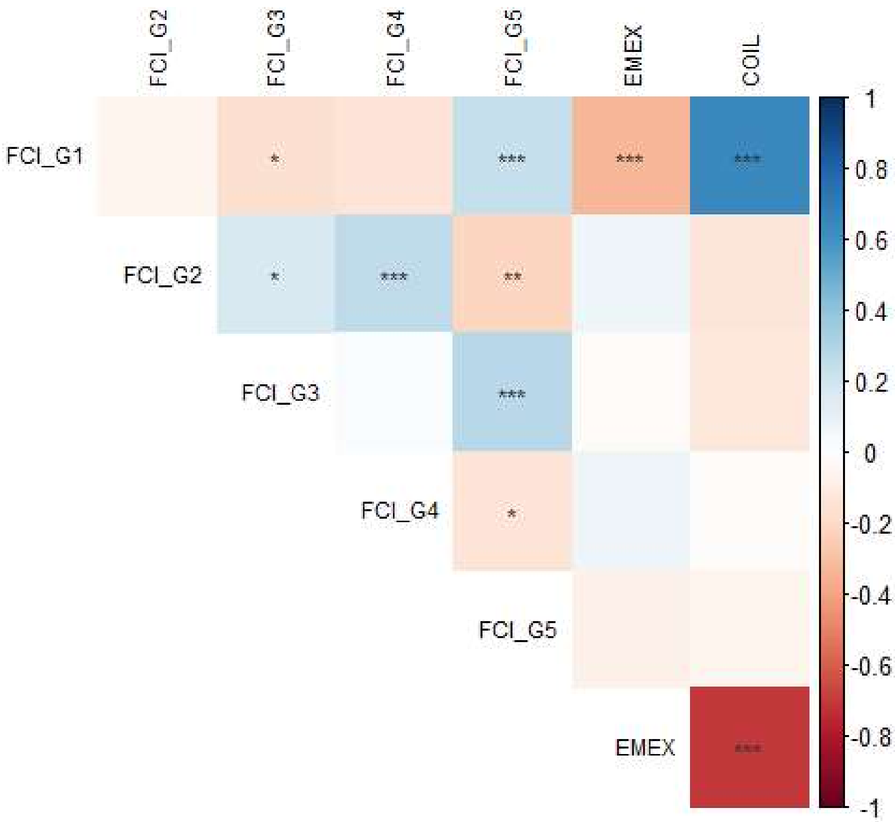


Figure 19 Simple correlations between cluster FCIs, US exchange rate (EMEX) and Oil Prices (COIL)
The red colour indicates a negative linear correlation, and the blue indicates a positive linear correlation.
Source: EMEX is the monthly USD nominal exchange rate against a basket of currencies of developing and emerging economies (OITP index) COIL is the monthly OIL Price Index from IMF Commodity Prices (Base year = 2016)

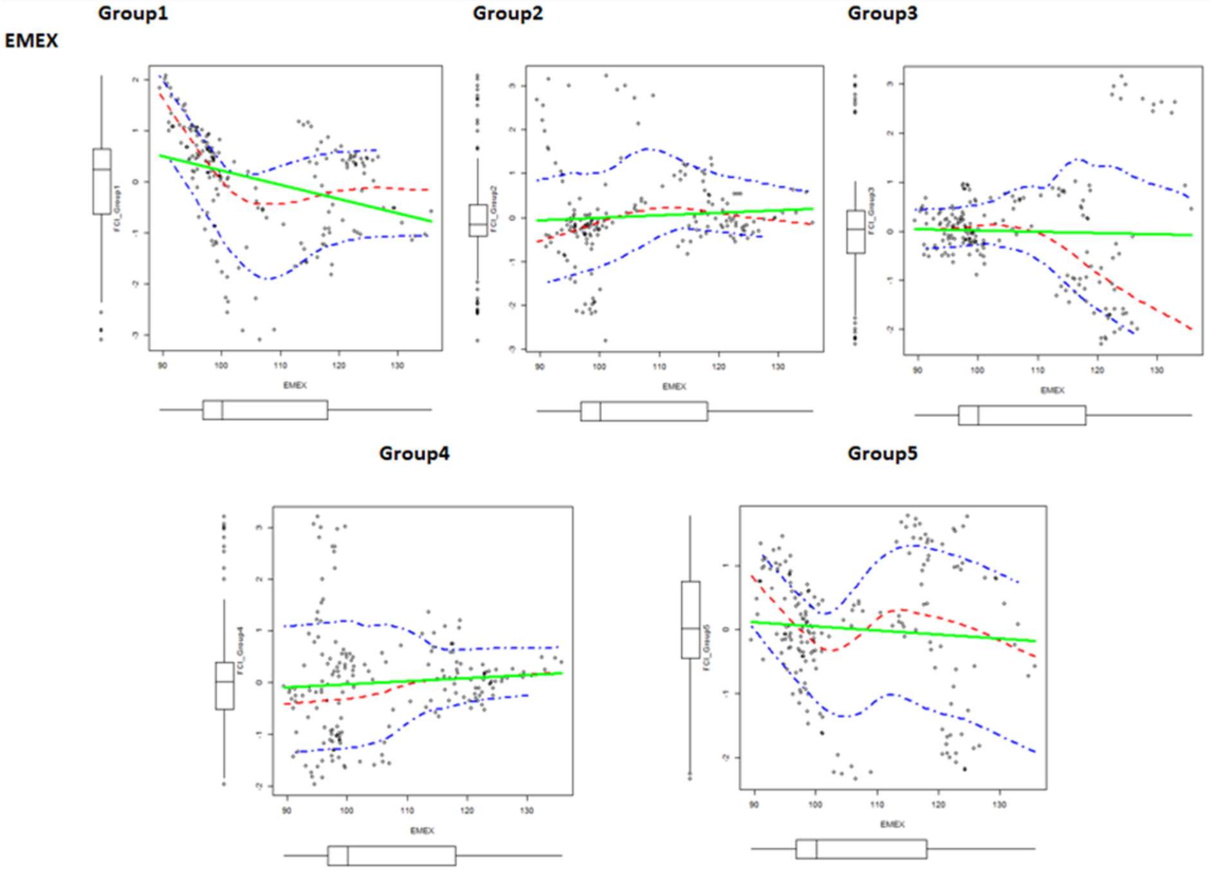


Figure 20 Relations between USD exchange rate (EMEX) and the cluster FCIS: OLS fit in green, non-parametric mean in red and non-parametric variance in blue
Source: EMEX is the monthly USD nominal exchange rate against a basket of currencies of developing and emerging economies (OITP index)

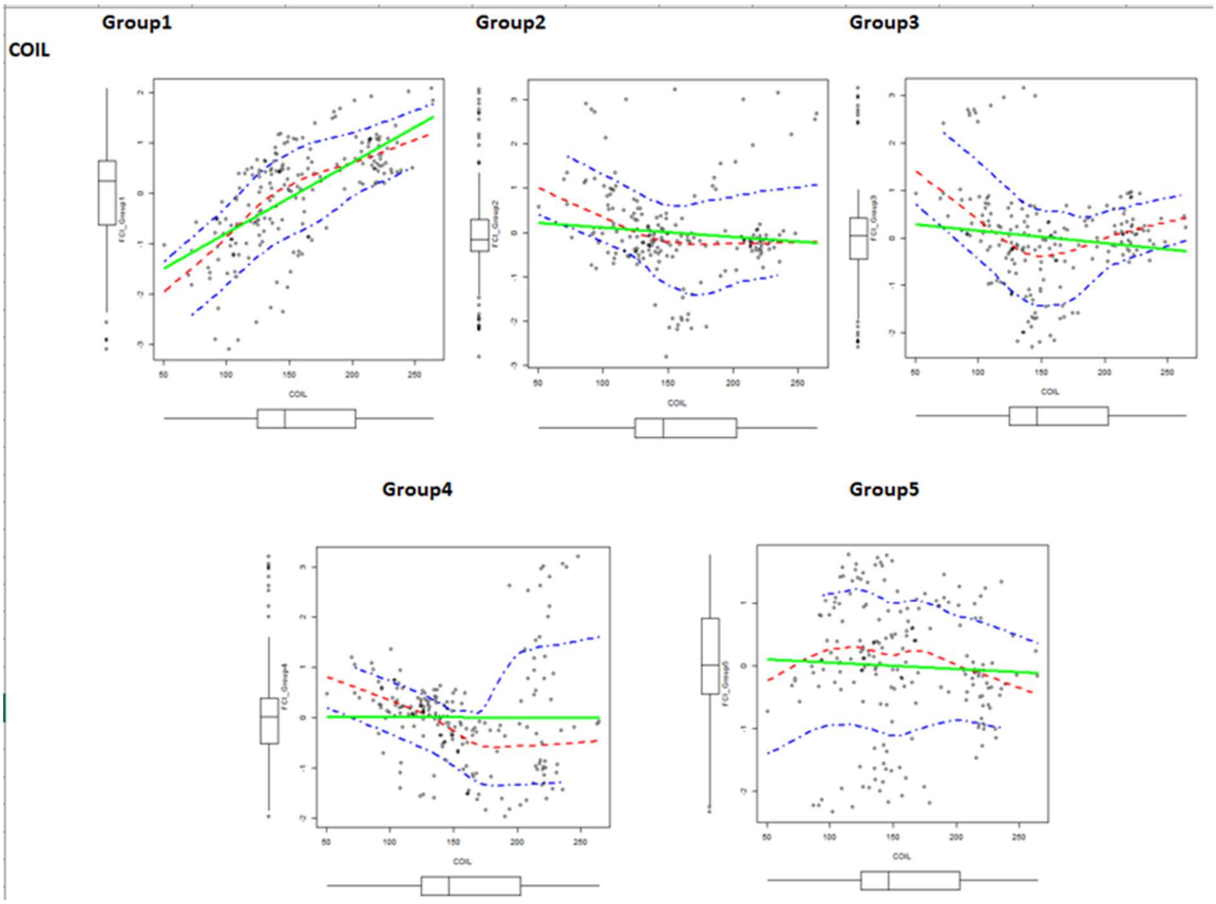


Figure 21 Relations between oil prices (COIL) and the cluster FCIS: OLS fit in green, non-parametric mean in red and non-parametric variance in blue
Source: COIL is the monthly Oil Price Index from IMF Commodity Prices (Base year = 2016)