Financial Conditions and Macroeconomic Volatility in Emerging Markets

Gian Paulo Soave*

Abstract

This paper assesses the role of financial conditions in the business cycles in emerging markets. Evidence from nonlinear VAR relating macroeconomic variables to proxies of financial conditions suggest that: (a) stressful times occur with considerable frequency, about 30% of time; (b) second moments of the main macroeconomic variables are regime dependent, with consumption and investment being more correlated with GDP and with larger volatility for all variables considered under financial distress conditions; (c) consumption is more volatile than GDP both under a regular financial condition and in a financial distress period; (d) the duration of the financial instability period is about 5 quarters; (e) and there are strong amplification effects related to the tightening of the credit conditions.

Keywords: Financial Conditions, Bayesian Panel VAR, Business Cycles

JEL - Classification: E32, E44, F41, F30, F34

Área ANPEC: 4 - Macroeconomia, Economia Monetária e Finanças

1 Introduction

One of the most striking aspects of the business cycles in emerging markets (EMs) is the pattern of the second moments of the macroeconomic data, particularly when compared to those of advanced economies (AEs): emerging economies experience much more substantial and frequent swings. Two empirical regularities can illustrate the differences between these groups: (i) GDP is twice as volatile in the EM group as in the AE group; (ii) consumption has a higher standard deviation than that of output in EMs, while the converse occurs in rich countries. (see, for example, Aguiar and Gopinath, 2007; Uribe and Schmitt-Grohé, 2017).

A large body of literature has been paying attention to the role of many distinct factors that could potentially account for these differences, e.g., less developed institutional environments, weaker economic policies, and greater dependence on (a few) commodities in EMs. However, almost all known episodes in the recent years of sharp movements in the international financial markets coincide with massive changes in the volatilities in such economies. Not surprisingly, recent researches have found a significant role played by the financial frictions in the business cycles in EMs. (see Akinci, 2017; Chang and Fernández, 2013; García-Cicco et al., 2010). Because the responses of these economies to financial instability seems more pronounced than in

*Post-Doctoral Research Associate - Universidade de São Paulo - FEARP/USP. Email: gianps@usp.br

AEs—at least on average—, the state of the financial conditions naturally emerges as a potential explanation for the observed differences between EMs business cycles and AEs.[1]

Accordingly, in this paper, I assess the consequences of "bad" financial conditions to the dynamic behavior of macroeconomic variables in EMs. To do so, I employ an econometric strategy that treats the financial conditions as an endogenous state variable, allowing to access the macroeconomic implications of distinct financial states. I fed a Bayesian Panel Threshold-VAR Model (BPT-VAR) with an estimated Financial Stress Index (FSI) for 25 EM economies and used it to analyze the implications of financial instability to the economy. Within the BPT-VAR, I define the regimes as two different states of nature indicated by the FSI: tranquil—or normal—times are situations in which the financial markets are relatively stable (low FSI), while stressful times—or financial distress—are periods of high financial instability (high FSI).[2] The BPT-VAR, with the embedded estimated financial instability indicators, endogenously estimates the threshold values at which each economy in the sample switches from one regime to another. These thresholds allow to separate the data into the two different regimes and to calculate regime-dependent impulse response functions and regime-dependent moments.

The results that emerge from the empirical analysis show that financial conditions are essential to understanding the business cycles in EMs, inducing strong non-linear effects. The findings can be synthesized through the following empirical regularities:

(i) emerging markets are prone to frequent regime switching in their financial conditions: stressful periods occur with a considerable frequency in the data ($\sim 30\%$ of the time);[3]

(ii) second moments of the main macroeconomic variables are regime dependent: first, consumption and investment correlations with GDP tend to be higher in financial distress periods. Second, volatility is much larger for the GDP, consumption, and investment in financial instability contexts. These patterns suggest that decisions become more dependent on the current income instead of the intertemporal—or permanent—income. Thus, financial frictions seems to be associated with raising credit constraints;

(iii) in both regimes, consumption is more volatile than the GDP;

(iv) the mean duration of financial distress periods is 5 quarters;

(v) conforming with the facts (ii), impulse responses are strongly regime dependent for most of the countries. Under financial instability conditions, consumption and investment responses tend to be strongly amplified. These findings are consistent with the notion of the *amplification effect* of financial frictions.

A critical problem when analyzing the empirical implications of financial instability to EMs business cycles is the limited data availability. I try to circumvent this problem by efficiently extracting information from the data: first, I construct a measure of financial conditions for each country using the method advocated in Koop and Korobilis (2014), which is more flexible then principal component methods as it is robust to gaps and unbalanced series. Second, I estimate the BPT-VAR through Bayesian Panel VAR methods (see, for example, Canova and Ciccarelli, 2013) assuming an hierarchical structure within each regime introducing a regime-

[1]For an extensive and detailed characterization of the Business Cycle properties of the emerging markets, see Uribe and Schmitt-Grohé (2017).

[2]Throughout the paper, I use the terms financial distress, financial instability or stressful times interchangeably.

[3]For a comparison, the so-called sudden stops are said to be rare events, occurring in less than 4% of time (see Calvo et al., 2006; Mendoza, 2010). The methodology employed here treats such events as extreme realizations of financial distresses.

specific exchangeable prior similar to Jarociński (2010).[4] Such a prior is convenient here since it express the beliefs that EMs share many features in terms of dynamics within regimes, and the Bayesian pooling exploits information from all countries to efficiently make the individual estimations, improving the accuracy when just a few observations are available for some country in a specific regime.[5]

A large body of literature has focused on business cycles in emerging markets, mainly motivated by the observed *excess volatility* of output and consumption in these economies. Many studies on this topic have used structural models in the spirit of Mendoza (1991), augmented with trend shocks in the spirit of Aguiar and Gopinath (2007) or with financial frictions, as in Neumeyer and Perri (2005), García-Cicco et al. (2010), Chang and Fernández (2013), and Mendoza (2010). This paper is particularly related to the latter branch of literature, aiming to assess the role of financial friction in those economies. However, in this paper, I focuses on characterizing business cycles from a reduced-form analysis perspective coupled with a detrending technique, which is an avenue taken by Agenor et al. (2000), Lane (2003), and Calderón and Fuentes (2010). Moreover, I use a unified framework for many countries that allows us to compare the impulse responses to shocks in GDP and in the financial conditions using a Bayesian Hierarchical Panel VAR structure similar to Ciccarelli and Rebucci (2006), Canova and Pappa (2007), Jarociński (2010), Canova and Dallari (2013), and Forero (2015). The only difference is that here the model features a nonlinear regime-switching structure.

The paper does not try to offer any explanation for the causes of financial instability in EMs. However, it is arguably important to understand the empirical implications of financial frictions for macro-variables as well as the degree of exposure of such economies to international financial shocks, which are my main focus.

The remainder of the paper is presented in three sections. Section 2 describes the methodology. Section 3 reports the results, and section 4 presents the conclusions.

2 Accessing Nonlinearities in the Emerging Markets Business Cycles

This section outlines the methods employed to estimate the threshold transition parameters for each country in the sample and describes how I extract the financial stress index from the data. I begin by describing the HTB-VAR model that implicitly links the exogenous estimated financial stress index to the economic activity. Then I present the procedure and the criteria to select a variable to be part of the financial condition indicator.

2.1 A Two-Regimes Bayesian Panel Threshold-VAR

I modeled each emerging economy as an individual threshold vector autoregressive (T-VAR) model. Although flexible, T-VAR models can suffer from high dimensionality, which is even more problematic for emerging markets because of the limited length of the time series. I

[4] Gelman et al. (see also 2003).

[5] As shown in Hsiao et al. (1999) and further in Gilhooly et al. (2012), linear VARs with such a prior can have very good small sample performance, even with only a few time series observations for each cross-sectional unit. As T-VARs are linear conditioned to a regime, the small sample properties of linear VARs with hierarchical prior schemes naturally extend to our contexts. Moreover, the BPT-VAR can be used within unbalanced panels, and thus is able to extract all information available.

overcome this problem by efficiently using the cross-sectional information within a regime. To do so, I combine the individual information with the cross-sectional information in each regime introducing a hierarchical structure setup. Importantly, the particular hierarchical structure, as represented by exchangeable priors, reflects the prior belief that countries tend to perform in a similar fashion within a certain regime, although there might be differences between regimes.

I assume that each country c, $c \in \{1, \cdots, C\}$, is represented by the following non-linear vector autoregressive equation:

$$\boldsymbol{y}_{c,t} = \begin{cases} \sum_{l=1}^{L^1} \boldsymbol{B}_{c,l}^{1\,\prime} \boldsymbol{y}_{c,t-l} + \boldsymbol{\Delta}_c^{1\prime} \boldsymbol{w}_t + \boldsymbol{\Gamma}_c^{1\prime} \boldsymbol{z}_{c,t} + \boldsymbol{u}_{c,t}^1 & \text{if} \quad y_{c,t-d_c}^{fsi} \leq y_c^* \\ \sum_{l=1}^{L^2} \boldsymbol{B}_{c,l}^{2\,\prime} \boldsymbol{y}_{c,t-l} + \boldsymbol{\Delta}_c^{2\prime} \boldsymbol{w}_t + \boldsymbol{\Gamma}_c^{2\prime} \boldsymbol{z}_{c,t} + \boldsymbol{u}_{c,t}^2 & \text{if} \quad y_{c,t-d_c}^{fsi} > y_c^* \end{cases} \tag{1}$$

for $t = 1, \cdots, T^c$, in which $y_{c,t}^{fsi} \in \boldsymbol{y}_{c,t}$ is the estimated FSI, where $\boldsymbol{y}_{c,t}$ is a vector of $K \times 1$ endogenous variables, $\boldsymbol{w}_{c,t}$ is a $W \times 1$ vector of exogenous variables common to all countries, and $\boldsymbol{z}_t$ is a $Z^c \times 1$ vector of exogenous variables in country c. The idiosyncratic threshold value, $y_c^* \in y_c^{fsi}$, and country-specific delay parameter, d_c, are unobservables and should be inferred from the data.

The reduced form regime-specific innovations $\boldsymbol{u}_{c,t}^r$, with $r = \{1, 2\}$, are assumed to be i.i.d. and to have a prior distribution $\boldsymbol{u}_{c,t}^r \sim N(0, \boldsymbol{\Sigma}_c^r)$. The coefficient matrices in a regime r, $\boldsymbol{B}_{c,l}^r$ and $\boldsymbol{\Gamma}_c^r$, are country-specific.

To clearly identify where an exchangeable prior will be applied, let us first rewrite the model in the following compact form:

$$\boldsymbol{Y}_c = \Big[\boldsymbol{X}_c \boldsymbol{B}_c^1 + \boldsymbol{Z}_c \boldsymbol{\Gamma}_c^1 + \boldsymbol{U}_c^1\Big] S_{c,t} + \Big[\boldsymbol{X}_c \boldsymbol{B}_c^2 + \boldsymbol{Z}_c \boldsymbol{\Gamma}_c^2 + \boldsymbol{U}_c^2\Big](1 - S_{c,t}), \tag{2}$$

where $S_{c,t} = 1 \iff y_{c,t-d}^{fsi} \leq y_c^*$, $\boldsymbol{Y}_c$,$\boldsymbol{X}_c$ and $\boldsymbol{Z}_c$ are, respectively, $T^c \times K$, $T^c \times M$ and $T^c \times Z^c$ matrices, where $M = Kp + W$. $\boldsymbol{B}_c^r$ is given by $\boldsymbol{B}_c^r = \begin{bmatrix} \boldsymbol{B}^{r\prime}{}_{c,1} & \cdots & \boldsymbol{B}^{r\prime}{}_{c,L^r} & \boldsymbol{\Delta}^{r\prime}{}_c \end{bmatrix}$ and $\boldsymbol{\Gamma}_c^r$ is a $(Z^c \times K)$ matrix. Letting $\mathbf{y}_c = vec(\boldsymbol{Y}_c)$, $\boldsymbol{\beta}_c^r = vec(\boldsymbol{B}_c^r)$, $\boldsymbol{\gamma}_c^r = vec(\boldsymbol{\Gamma}_c^r)$ and $\boldsymbol{u}_c^r = vec(\boldsymbol{U}_c^r)$, then (2) can be conveniently restated as

$$\mathbf{y}_c^r = (\mathbf{I}_m \otimes \mathbf{X}_c^r)\boldsymbol{\beta}_c^r - (\mathbf{I}_m \otimes \mathbf{Z}_c^r)\boldsymbol{\gamma}_c^r + \boldsymbol{u}_c^r, \quad r = \{1, 2\} \tag{3}$$

where $u_c^r \sim N(0, \boldsymbol{\Sigma}_{\boldsymbol{r}} \otimes \mathbf{I}_m)$. Given the normality of the error term, in order to have a normal posterior, I assume a conjugated prior that is also an exchangeable prior for each country c, given by

$$p(\boldsymbol{\beta}_c^r | \bar{\boldsymbol{\beta}}^r, \boldsymbol{\Lambda}_c) = N(\bar{\boldsymbol{\beta}}^r, \boldsymbol{\Lambda}_c^r) \tag{4}$$

where $\bar{\boldsymbol{\beta}}^r$ is the common mean within the regime r and variance $\boldsymbol{\Lambda}_c^r$ will discussed in detail in the section below. Here, it is important to highlight that the above expression clarifies that the parameters that I am interested in are assumed to be drawn from the same data generating process. Our economic interpretation is that the underlying forces connecting variables in $\mathbf{y}_c$ are likely to be similar in our sample of emerging markets. For the remaining parameters, I assume that $p(\bar{\boldsymbol{\beta}}_c^r) \propto p(\boldsymbol{\gamma}_c^r) \propto 1$ and a standard diffuse prior for the regime dependent variances:

$$p(\boldsymbol{\Sigma}_c^r) \propto |\boldsymbol{\Sigma}_c^r|^{-\frac{1}{2}(N+1)}$$

2.1.1 The Minnesota-Style Prior and Cross-Sectional Shrinkage

For the variances $\boldsymbol{\Lambda}_c^r$ I follow Jarociński (2010) in specifying a Minnesota-like prior given by $\lambda^r \boldsymbol{L}_c$, where:

$$\boldsymbol{L}_c = \frac{\boldsymbol{\sigma}_{cn}^2}{\boldsymbol{\sigma}_{ck}^2}$$

The only difference from Jarociński's scheme is that I assume λ to be regime-specific. The prior for this parameter is given by:

$$p(\lambda|s,v) = IG_2 \propto \lambda^{-\frac{v+2}{2}} \exp\left(-\frac{1}{2}\frac{s}{\lambda}\right) \tag{5}$$

Under such a prior, Jarociński (2010) shows that the posterior for λ is given by:

$$p(\lambda_r|s,v) = IG_2 \propto \lambda_r^{-\frac{CNK+2}{2}} \exp\left(-\frac{1}{2}\frac{s + \sum_C \sum_K \sum_N \left[\boldsymbol{\beta}_c^r(k,n) - \bar{\boldsymbol{\beta}}^r(k,n)\right]^2 / \left(\frac{\boldsymbol{\sigma}_{cn}^2}{\boldsymbol{\sigma}_{ck}^2}\right)}{\lambda_r}\right)$$

2.1.2 Non-Linear Impulse Responses

To analyze the dynamic responses of the variables in this nonlinear context, we must take into account both history and the possibility of a regime switch. These requirements are at odds with traditional impulse response functions present in linear VARs since, by construction, they are symmetrical and history-independent of the current state of the business cycles. To better capture the nonlinear nature of the TVARs, I make use of the generalized impulse response (GIRF) proposed by Koop et al. (1996), defined as:

$$GIRF_y(h, \varepsilon_t, \mathcal{H}_{t-1}) = E[Y_{t+h}|\varepsilon_t, \mathcal{H}_{t-1}] - E[Y_{t+h}|\mathcal{H}_{t-1}] \tag{6}$$

where h is the length of the simulation horizon and $\mathcal{H}_{t-1}$ is the history in period t.[6]

A concise outline of how to estimate the GIRF in a Bayesian VAR context is as follows: given a period-t shock, ε_t, and the history of what happened within the system until $t-1$, $\mathcal{H}_{t-1}$, take the i-th draw from the Gibbs sampler of the parameters of the model, e.g. $\Theta^{(i)}$. For each draw, compute $GIRF_y(h, \varepsilon_t, \mathcal{H}_{t-1}|\Theta^{(i)})$ for a hundred of possible paths. Then, all we have to do is to integrate over $\Theta^{(i)}$. To do so, we estimate $GIRF_y$ simply by computing

$$G\hat{IR}F_y(h, \varepsilon_t, \mathcal{H}_{t-1}) = \frac{1}{D}\sum_{i=1}^{D} GIRF_y(h, \varepsilon_t, \mathcal{H}_{t-1}|\Theta^{(i)})$$

where D is the number of draws. As stressed by Galvão and Owyang (2014), the GIRF in a nonlinear context measures the effects of a one-standard-deviation shock to a selected variable on the endogenous variables, assuming a specific set of histories at the impact. In practice, note that we can calculate $GIRF_y(h, \varepsilon_t, \mathcal{H}_{t-1})$ for specific events in $\mathcal{H}_{t-1}$, which means that we can condition the estimates for each regime, thus obtaining regime dependent impulse responses. Moreover, the GIRFs are defined so that the regime can chance over horizon.

[6]From now on, I use term impulse response meaning generalized impulse response functions.

The algorithm to compute (1) under the assumed priors is presented in the appendix C. As the GIRFs are computed for a given draw of the parameters vector, the confidence band can be based on the uncertainty from parameters if we are interested in the idiosyncratic estimation. However, as I focus on the average (panel) response, I compute confidence band based on the median impulse response for each country. In the next section, I discuss the method used to estimate the financial conditions for each emerging market to feed the BPT-VAR model.

2.2 The Financial Stress Index

A financial stress index (FSI) is intended to be a broad measure reflecting the current state of the financial markets. Such an index is constructed as a continuous variable where financial crises are at one extreme, and normal financial conditions are at the other. Usually, a FSI is based on a combination of many financial stress indicators for specific markets, with each of them constructed from many different observable variables, which enables the index to represent the whole financial system with one single measure.

Methods for extracting from data the information that can synthesize the state of financial markets are now well-established. They are usually based on principal component methods, as in Hatzius et al. (2010), sub-index weighting schemes similar to Cardarelli et al. (2009), or the Kalman Filter coupled with advanced weighting schemes, as in Koop and Korobilis (2014). No matter what kind of method is used, the construction of a FSI faces identification problems. Moreover, one may face difficulties in choosing which sub-index should be included in the broader index, as well as in deciding what variable can best represent a particular sub-index.

When constructing such a FSI for many countries, a common practice in the literature is to limit the number of variables composing a sub-index—instead of using as many as possible—. This is done for two main reasons: (i) data availability, which may be scarce when dealing with emerging markets, and (ii) comparability.

Concerning (i), one can take advantage of the existence of common factors driving the financial markets, so that even a few variables may contain the most relevant information about the common components. Thus, the marginal gain of information is a decreasing function of the number of variables. When it comes to (ii), comparability is desired when one aims to analyze the effects of global shocks and spillover effects on countries, as in Cardarelli et al. (2009) for advanced economies and as in Balakrishnan et al. (2011) for emerging markets. In the present case, we need a comparable proxy so that the central distribution of the common coefficients is unaffected by the index.

My measure of financial stress in emerging markets closely follows that proposed by Balakrishnan et al. (2011) for emerging economies. The authors argue that an emerging market is likely to be influenced by financial stresses coming from international markets —in particular, from advanced economies and other emerging economies. Changes in factors such as global GDP growth and prices such as interest rates can have a substantial impact on the financial conditions within an emerging market. On the other hand, a country-specific factor expressed by the degree of financial and trade linkages and macroeconomic vulnerabilities can make a country more exposed to a financial stress period.

However, while I follow Balakrishnan et al. (2011) in constructing and selecting the variables to be included in our measure of financial conditions, I extract the information from the data employing the method proposed by Koop and Korobilis (2014). Such a method have many advantages compared to the pure principal component methods widely used in the literature. First, it account for an unbalanced set of financial variables, a recurrent problem when it comes to emerging economies—in which data is frequently scarce prior to 2000. Second, the method takes into account that an ideal financial stress index should only express shocks on the financial system, as emphasized by Hatzius et al. (2010). This can be done by estimating a system of equations containing not only financial variables but also macroeconomic variables expressing the macroeconomic environment so that the macroeconomic information is purged from the estimated index. Third, the weights are calculated from the data, so that the researchers can stay agnostic from each of the financial variables that should be included at a specific moment of time.[7] The appendix is devoted to presenting the method used in more detail.

I construct a Financial Stress Index for all countries for which I have sufficient data. Following the suggestions by Balakrishnan (2011), our measure includes the following sub-indexes:

Banking Sector Stress - FCI.1

(i) **Banking Sector-β** - This measure, given by the ratio of bank share prices to total share prices, aims to isolate the stress of the banking sector in terms of the whole economy. It is our first choice sub-index to measure banking sector stress and is given by:

$$\beta_{c,t} = \frac{cov(r^m_{c,t}, r^b_{c,t})}{var(m)},$$

where r^b and r^m are the returns to the banking sector stock index and the overall stock index. A value $\beta > 1$ means that the banks are relatively riskier compared the average volatility of the other markets. I estimate β using monthly data from DataStream based on a twelve-months rolling window, assigning a value of 1 when $\beta > 1$ and 0 otherwise. The overall return is proxied by the return of the S&P500.

(ii) **Bank Spreads** For countries with unavailable data to compute $\beta_{c,t}$, I measure the stress in the banking sector using the spread in the loan versus deposit rates using data from the IFS.

Foreign Market Pressure - FCI.2 To capture instabilities in the exchange markets, I use the exchange market pressure Index (EMPI) proposed by Eichengreen et al. (2004), which is defined as

$$EMPI_{c,t} = \left(\frac{\Delta e_{c,t} - \mu_{c,\Delta e}}{\sigma_{c,\Delta e}}\right) - \left(\frac{\Delta R_{c,t} - \mu_{c,\Delta R}}{\sigma_{i,\Delta R}}\right)$$

where Δ is the monthly variation, μ is the mean value, σ is the standard deviation, e is the nominal exchange rate of local currency per dollar, and R stands for the reserves.

Equity Market Volatility - FCI.3 and - FCI.4 For the Equity Market, I use two sub-indexes.

(i) **FCI.3** Following Balakrishnan et al. (2011), I proxied the stress surrounding the security markets by the negative of the annual variation of the overall index in country c, given by

[7]Moreover, although the computations are much more complex compared to a pure principal component method, the method proposed by the authors is quite fast under certain setups. Combined with the high flexibility, computation cost is another reason why I choose not to include the financial stress measure as another layer in our TVAR. For example, the methods proposed by Lopes and West (2004) could be employed as additional equations in the Gibbs sampler, but the computational burden would be increased.

$\Delta^{12} y_c = y_{c,t} - y_{c,t-12}$, where y_c is the overall index in country c in period t.

(ii) **FCI.4** The second sub-index attempts to capture the effects of expected loss, risk, or uncertainty about firms' future profits. An increase is expected in this variable when the likelihood of a financial stress period increases. To construct this measure, I estimate simple GARCH(1,1) models for each of the emerging economies in our sample using the following process:

$$\sigma^2_{c,t} = \omega + \phi_{c,1}\varepsilon^2_{c,t-1} + \phi_{c,2}\sigma^2_{c,t-1} + \epsilon_{c,t}$$

where σ^2_t is the variance of a regression of an AR(1) regression for the overall equity price index.

Sovereign Debt Stress - FCI.5

(i) **EMBI+** The EMBI+, as calculated by J.P.Morgan, is our preferred measure of stress related to sovereign debts.

(ii) **Sovereign Spread 1** For countries where EMBI+ is unavailable or to short, I use the spread between the interest rate on sovereign debt in country c and 3-month USA bonds.

(iii) **Sovereign Spread 2** Alternatively, I use the spread between security markets in country c compared to the USA.

(iv) **Sovereign Spread 3** Finally, for countries with gaps in EMBI+, I fill the missing data using credit default swaps (CDS) data.

3 Estimations and Empirical Findings

The datasets used in this paper are presented in Tables 5 and 6 in the appendix. They encompass financial as well macroeconomic data from a set of 25 emerging economies. The only criterion for a country to be selected is data availability. For the FSI, I use monthly data to construct the sub-indexes described in the previous section and take the quarterly average after ensuring that the series are stationary and free of seasonality effects. For the GDP, consumption, and investment, I use the logarithm of the real values and compute deviations from a trend (HP-Filter and BN-Filter proposed by Grant and Chan (2017) and Kamber et al. (2018), respectively). As the data come from many different sources and are of different time spans, I refer the reader to the aforementioned tables to access detailed information.

Lets start by presenting the results for the FSIs. As suggested by the visual inspection of Figure 1, the frequency of financial stress periods in EMs seem quite high. Importantly, there are clearly two distinct pictures. Prior to 2004, financial instability appeared to be governed by both international and idiosyncratic forces. From 2004 onwards, the international markets' condition seems to be the most important determinant of financial stability. However, a comprehensive study of the determinants of the FSI in EMs is out of the scope of this paper. For the interested reader, I refer to Balakrishnan et al. (2011) and Park and Mercado (2014). Plots of the individual series are available upon request.

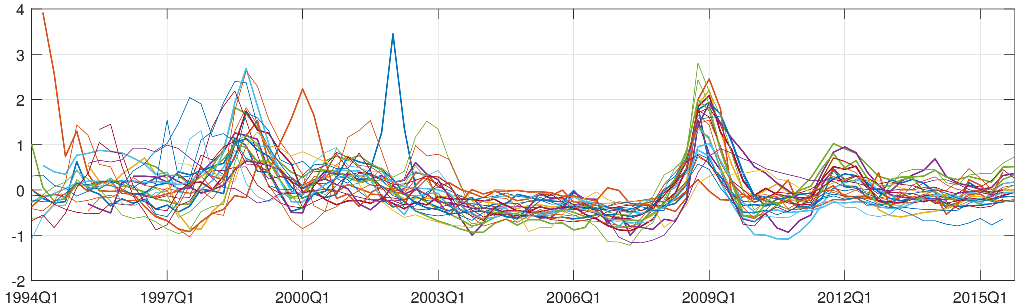


Figure 1: Estimated FSI for all countries in the sample

To analyze the implications of financial instability and how it dynamically affects an emerging economy, I estimate the BPT-VAR embedded with the estimated FSIs. I setup each VAR equation as follows:

$$\boldsymbol{y}_{c,t} = \begin{bmatrix} y_{c,t} \\ c_{c,t} \\ i_{c,t} \\ fsi_{c,t} \end{bmatrix}$$

where $y_{c,t}$ is GDP, $c_{c,t}$ is consumption, $i_{c,t}$ is investment and $fsi_{c,t}$ is the financial stress index. Because of the limited time span, I restricted the maximum lag to 3, with Bayesian information criterion (BIC) favoring a BPT-VAR with one lag. Using the priors described in section 2.1, settled under a fairly loose scheme, I ran the Bayesian algorithm to search for endogenous regime-switching in the sample. The results are expressed in Figure 4 in the appendix and are summarized in Table 1.

Table 1: Financial Instabilities in EMs: Properties

Measure — Detrending technique	HP[1]	BN[2]
Quarters in a financial distress regimes in the data	30.27%	30.10%
Duration (mean # of quarters after a crisis begins)	4.87	4.94

[1] HP filter computed as in Grant and Chan (2017)
[2] Beveridge-Nelson decomposition using the method of Kamber et al. (2018)

From the BPT-VAR estimates, EMs are economies prone to frequent financial instabilities that may have consequences for macroeconomic variables. In the sample, a typical emerging economy switches from one regime to another about 30% of the time. Moreover, when a crisis begins, it takes about one and a half years for the economy to return to a stable financial condition.

Turning to the analyses of the empirical implications of financial distress, I use the estimated unobservable threshold parameters for each EM in the sample to separate each time series into periods of financial instability and periods of tranquility. Then, using the separated time series, I compute the regime-dependent moments —i.e., business cycle moments within regimes—and compare them between regimes. The results are expressed in Table 2.

Financial frictions have serious implications for EMs, affecting the business cycles in a nonlinear fashion. For moments, there are two major consequences: first, correlations of consumption and investment with the GDP tend to be higher in financial instability regimes relative to tranquil times. The relative correlation between regimes for consumption is about 0.97 and is 0.865 for investment. Although the result for consumption may be an artifact of the

Table 2: Emerging Markets Business Cycles

Correlations					
Within regimes	HP[1]	BN[2]	Relative	HP	BN
$\rho_1(c,y)$	0.603	0.570	$\frac{\rho_1(c,y)}{\rho_2(c,y)}$	0.980	0.961
$\rho_1(i,y)$	0.648	0.495			
$\rho_2(c,y)$	0.615	0.593	$\frac{\rho_1(i,y)}{\rho_2(i,y)}$	0.882	0.843
$\rho_2(i,y)$	0.734	0.704			
Standard deviations					
Within regimes	HP	BN	Relative	HP	BN
$\sigma_1(y)$	0.019	0.013	$\frac{\sigma_1(y)}{\sigma_2(y)}$	0.711	0.722
$\sigma_1(c)$	0.024	0.016			
$\sigma_1(i)$	0.085	0.055	$\frac{\sigma_1(c)}{\sigma_2(c)}$	0.690	0.648
$\sigma_2(y)$	0.027	0.018			
$\sigma_2(c)$	0.036	0.025	$\frac{\sigma_1(i)}{\sigma_2(i)}$	0.552	0.473
$\sigma_2(i)$	0.155	0.117			
Standard deviations relative to GDP					
Regime 1	HP	BN	Regime 2	HP	BN
$\frac{\sigma_1(c)}{\sigma_1(y)}$	1.241	1.230	$\frac{\sigma_2(c)}{\sigma_2(y)}$	1.291	1.386
$\frac{\sigma_1(i)}{\sigma_1(y)}$	4.370	4.235	$\frac{\sigma_2(i)}{\sigma_2(y)}$	5.632	6.325

[1] HP filter computed as in Grant and Chan (2017)
[2] Beveridge-Nelson decomposition using the method of Kamber et al. (2018)

small sample, the difference for investment is substantial. The volatility implications are less subtle. As one can expect, the volatility in a financial distress regime is much more pronounced than in a normal regime. While the GDP tends to show an average increase of about 39% in volatility in times of stress, consumption volatility magnifies by about 49% and investment by about 95%, on average.[8]

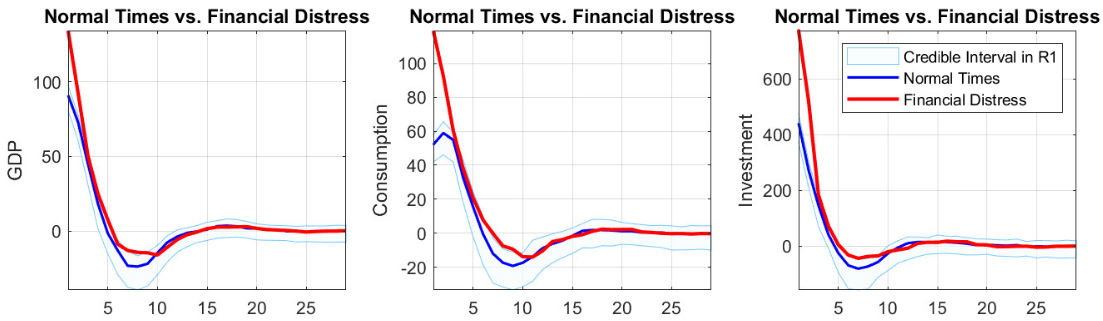
I also investigate whether the standard deviations of consumption and investment change between regimes relative to the standard deviation of the GDP. This analysis is of interest since it can shed some light on how intertemporal decisions are affected by tighter credit constraints. The results, presented at the bottom of Table 2, show that as financial conditions deteriorate, consumption and investment become even more volatile than the GDP. This means that households and firms may face more difficulty in anticipating future income to buy consumption and investment goods. These results echos those of the literature on the phenomenon called *excess volatility*. Here, under financial distress, the *excess volatility* worsens.

The better understand how financial frictions translate to the dynamics of macro-variables, I now simulate shocks on the GDP and FSI and compute the GIRFs. The GIRFs are computed within a regime but allowing for the possibility of a regime-switch. Starting with the histories in one regime for a certain country, I simulate the evolution of the VAR system for 40 quarters

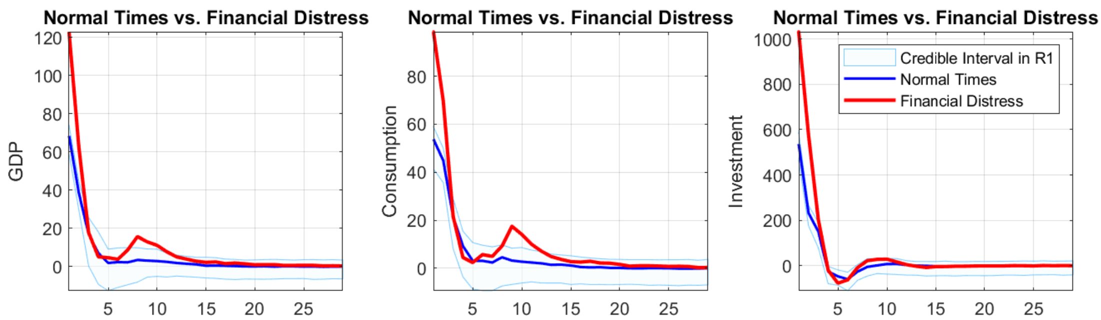
[8] These results are simple averages from the two filter methods. The term "about" is used to express both the estimation and filter uncertainties.

with and without the shock of interest, compute the differences between the simulated paths, and take the average responses. In such a context, the GIRF measures the responses of the endogenous variables to a shocked variable at some horizon h within a specific regime r. The confidence band is calculated from the draws of the VAR coefficients from the last 1,000 draws in the Metropolis-within-Gibbs-sampler.

Lets first analyze the effects of a positive shock of one standard deviation on the GDP gap. The results are expressed in Figures 2. The first and most interesting point to note is that, for almost all of the cases, the non-linear effects previously identified in business cycle moments are also expressed in the GIRFs.[9] Second, there are clearly heterogeneous responses both within regimes as well as between regimes.



(a) HP as proposed in Grant and Chan (2017)



(b) BN as proposed in Kamber et al. (2018)

Figure 2: Responses for a positive shock on GDP for selected countries. Blue line: normal regime. Red line: financial distress. Confidence interval for financial distress periods omitted for simplicity.

To be specific about the nonlinear effects found in the data, the responses in the financial distress regime are much larger than in the normal regime. Since accounting for these differences by looking at such a large number of plots can be cumbersome, I calculate a measure of the mean amplification effects in the sample caused by the presence of financial friction. I do so by taking the mean difference between the responses in regimes 2 (stressful times) and 1 (normal times). A positive sign means that the response in regime 2 is more pronounced than in regime 1, assuming that both have the same sign. I compute the differences both *at impact*—meaning the impact in the first period—and on the cumulated impact, calculated from the cumulative impulse responses. The results are shown in Table 3 expressed via the mean differences in the sample. At impact, the responses of the GDP tend to be almost 89.8% higher in regime 2. For the consumption, the difference is somewhat lower compared to the case of the GDP but still quite pronounced: approximately 79.4% higher in regime 2. For investment, the difference

[9]As the impulses are calculated from different histories and coefficients, the superposition of confidence interval is for illustration purposes, only.

between the regimes rises dramatically, reaching 134.4%. When the effects are cumulatively summed over all of the simulated horizon, we see that the differences continue to increase. Our result suggests a large *amplification effect* due to the presence of financial frictions, which is in line with the financial accelerator literature (see, for example, Bernanke et al., 1999; Kiyotaki and Moore, 1997).

Table 3: Amplification: Mean Difference Between Regimes

At Impact	Sign	Mean Difference
GDP	+	54.89%
Consumption	+	84.42%
Investment	+	89.48%
Cumulated	**Sign**	**Mean Difference**
GDP	+	144.18%
Consumption	+	154.40%
Investment	+	315.95%

Note: At impact and cumulated mean difference between regimes after a GDP shock. Results based on HP-Filter from Grant and Chan (2017).

I repeat the previous exercise, but now for a positive one standard deviation shock on the financial instability proxy. This shock is interpreted as worsening the financial conditions in a specific regime. For brevity, the results are expressed for only four countries in Figure 3. As the GIRFs make clear, poor financial conditions are pervasive to EMs. As the credit conditions worsen, independently of the regime, GDP, consumption, and investment fall. Specifically, the effects in regime 2 are more pronounced than in regime 1, with some countries experiencing severe impacts, as in Malaysia and Romania in the figure. Complementing these findings, table 4 shows the mean differences in the responses both at impact and cumulated for the simulated horizon. For the sample as a whole, tightening financial conditions—captured by a positive shock to the Financial Stress Index—reduces the GDP, consumption, and investment in both regimes. The negative effects are again more intense in the financial distress regime.

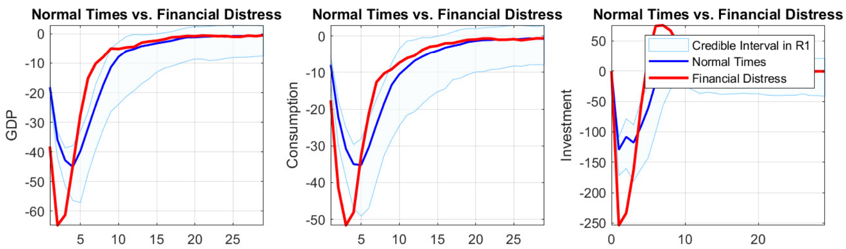


Figure 3: Responses for a positive shock on FSI for selected countries. Blue line: normal regime. Red line: financial distress. C.I.: Confidence Interval for the normal regime.

Table 4: Difference in Responses Between Regimes

At Impact	Sign	Mean Difference
GDP	+	31.14%
Consumption	+	81.78%
Investment	+	70.48%
Cumulated	**Sign**	**Mean Difference**
GDP	+	11.55%
Consumption	+	15.62%
Investment	+	17.69%

Note: At impact and cumulated mean difference between regimes after a financial shock. Results based on HP-Filter from Grant and Chan (2017).

Therefore, not only do the financial conditions imply regime switches with remarkable frequency in the emerging economies, but also adverse financial shocks are propagated in a very nonlinear and asymmetrical fashion in these economies.

4 Conclusion

This paper provides an empirical characterization of the dynamics imposed by financial instability periods to the emerging markets' business cycles. In a first step, I estimate a Financial Stress Index (FSI) by employing dynamic factor methods and show that financial markets in emerging economies frequently feature events of financial instability. Then, in a second step, I use a Bayesian Panel Threshold VAR (BPT-VAR) model fed with the FSI estimated for each country in the sample (25 emerging economies) to estimate a transition variable indicator that indicates whether the economy is under a normal financial stability or under a financial distress period.

The results suggest that financial instability may affect both the correlations and the volatilities of two important macro-aggregates, consumption and investment, and can also generate enormous asymmetries between regimes. In summary, when economies experience tranquil times and good conditions in financial markets, their business cycle properties are remarkably different from those in a financial distress period. During such events, EMs tend to be much more volatile, and such behavior has implications not only for the second moments of the data but also for the dynamics of the macro-variables. Moreover, shocks are propagated in a regime-dependent fashion: in a financial instability regime, shocks to GDP have a larger (much larger, in some cases) effect on real variables such as output, consumption, and investment. Thus, I interpret these results as suggesting that financial frictions play a crucial role in the business cycles in emerging markets. Within different channels, the amplification effects seems to be crucial.

Finally, it is important to point out that analysis here has important policy implications. Policymakers in EMs may wish to introduce policies trying to reduce the likelihood and magnitude of a financial crisis. From a theoretical point of view, one of such policies would be a macroprudential capital control in the spirit of Jeanne and Korinek (2010) and Bianchi and Mendoza (2017). In practice, such policies would require monitoring the leverage ratio in booms and bust levying tax to affect the incentives of the agents to take on debt in riskier times.

A Appendix

Figure 4: Regime-switching in some countries in the sample

B Posterior Distribution of Prior Hyper-Parameters in Each Regime

The posterior distribution of the parameter λ_r is the tightness of the prior distribution of the VAR coefficients for a regime r. Following Gelman (2006), we use a fairly loose prior to allow the data speak. As suggested by Figure 5, the degree of cross-sectional shrinkage is similar and well identified in the two regimes.

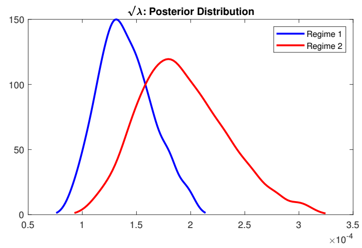


Figure 5: λ_i: Cross-sectional shrinkage similarities between regimes.

C Bayesian Estimation: Metropolis-within-Gibbs Algorithm

The algorithm starts with individual OLS estimations of linear-VARs, keeping $\boldsymbol{\Sigma}_c$, $\boldsymbol{L_c}$, and $\boldsymbol{\beta_c}$ and the starting value $\bar{\boldsymbol{\beta}} = \frac{1}{C}\sum_{c=1}^{C} \boldsymbol{\beta}_c$. The Gibbs sampling with a Metropolis step is performed as follow:[10]

1. Draw from $p(\lambda_r|\Theta/\lambda_r, \mathbf{Y})$, for regime r, where

$$\lambda_r|\Theta/\lambda_r, \mathbf{Y} \sim IG_2\left(s + \sum_{c=1}^{C}\sum_{k=1}^{K}\sum_{n=1}^{N}\left[\boldsymbol{\beta}_c^r(k,n) - \bar{\boldsymbol{\beta}}^r(k,n)\right]^2\left(\frac{\hat{\boldsymbol{\sigma}}_{cn}^2}{\hat{\boldsymbol{\sigma}}_{ck}^2}\right), v + CNK\right)$$

   and compute $\boldsymbol{\Lambda}_c^r = \text{diag}(\text{vec}(\lambda^r \boldsymbol{L}_c))$

2. Draw from $p(\bar{\boldsymbol{\beta}}_r|\Theta/\bar{\boldsymbol{\beta}}_r, \mathbf{Y})$, where

$$\bar{\boldsymbol{\beta}}_r|\Theta/\bar{\boldsymbol{\beta}}_r, \mathbf{Y} \sim N(\bar{\bar{\boldsymbol{\beta}}}_r, \boldsymbol{\Lambda}_1^r)$$

$$\bar{\bar{\boldsymbol{\beta}}}_r = \left(\sum_{c=a}^{C}(\boldsymbol{\Lambda}_c^r)^{-1}\right)^{-1}\left(\sum_{c=a}^{C}(\boldsymbol{\Lambda}_c^r)^{-1}\boldsymbol{\beta}_c\right)$$

$$\boldsymbol{\Lambda}_1^r = \left(\sum_{c=a}^{C}(\boldsymbol{\Lambda}_c^r)^{-1}\right)^{-1}$$

3. Draw from $p(\boldsymbol{\Sigma}_c^r|\Theta/\boldsymbol{\Sigma}_c^r, \mathbf{y}_c)$, where

$$\boldsymbol{\Sigma}_c^r|\Theta/\boldsymbol{\Sigma}_c^r, \mathbf{y}_c \sim \text{IW}\Big((\boldsymbol{u}_c^r)'(\boldsymbol{u}_c^r), T_c^r\Big)$$

[10] I run the sampler with 1,000,000 draws, discarding the first 50,000 to minimize the effects of the initial values.

4. Draw from $p(\boldsymbol{\gamma}_r|\Theta/\boldsymbol{\gamma}_r, \mathbf{y}_c)$, where

$$\boldsymbol{\gamma}_r|\Theta/\boldsymbol{\gamma}_r, \mathbf{y}_c \sim N(\bar{\boldsymbol{\gamma}}_c^r, \boldsymbol{\Lambda}_2^r)$$

$$\bar{\boldsymbol{\gamma}}_c^r = ((\boldsymbol{\Sigma}_c^r)^{-1} \otimes \boldsymbol{Z}_c{}'\boldsymbol{Z}_c)^{-1}(\boldsymbol{I} \otimes \boldsymbol{Z}_c{}')((\boldsymbol{\Sigma}_c^r)^{-1} \otimes \boldsymbol{I})(\boldsymbol{y}_c - (\boldsymbol{I} \otimes \boldsymbol{X}_c))\boldsymbol{\beta}_c^r$$

$$\boldsymbol{\Lambda}_2^r = ((\boldsymbol{\Sigma}_c^r)^{-1} \otimes \boldsymbol{Z}_c{}'\boldsymbol{Z}_c)^{-1}$$

5. Draw from $p(\boldsymbol{\beta}_c^r|\Theta/\boldsymbol{\beta}_c^r, \mathbf{y}_c)$, and check for stability. Otherwise, discard it, where

$$\boldsymbol{\beta}_r|\Theta/\boldsymbol{\gamma}_r, \mathbf{y}_c \sim N(\bar{\boldsymbol{\beta}}_c^r, \boldsymbol{\Lambda}_3^r)$$

$$\bar{\boldsymbol{\beta}}_c^r = ((\boldsymbol{\Sigma}_c^r)^{-1} \otimes \boldsymbol{X}_c{}'\boldsymbol{X}_c + (\boldsymbol{\Lambda}_3^r)^{-1})^{-1}(\boldsymbol{I} \otimes \boldsymbol{X}_c{}')((\boldsymbol{\Sigma}_c^r)^{-1} \otimes \boldsymbol{I})(\boldsymbol{y}_c - (\boldsymbol{I} \otimes \boldsymbol{Z}_c))\boldsymbol{\gamma}_c^r + (\boldsymbol{\Lambda}_c^r)^{-1}\bar{\boldsymbol{\beta}}^{\boldsymbol{r}})$$

$$\boldsymbol{\Lambda}_3^r = ((\boldsymbol{\Sigma}_c^r)^{-1} \otimes \boldsymbol{X}_c{}'\boldsymbol{X}_c + (\boldsymbol{\Lambda}_c^r)^{-1})^{-1}$$

6. Draw from $p(y_c^*|\Theta/y_c^*, \mathbf{y}_c)$ using an adaptive random walk Metropolis scheme. Following Alessandri and Mumtaz (2013), we set the mean of the prior as the mean value of y_c^* for each c with a value of 10 for variance.

7. Draw from $p(d_c|\Theta/d_c, \mathbf{y}_c)$ from a discrete distribution, with candidates $d_c = 1, 2, 3, 4$. The algorithm is provided by Chen and Lee (1995).

8. Repeat steps 3 to 7 for $c = 1, \cdots, C$.

9. Repeat steps 1 to 7 for $r = 1, 2$.

D Estimation of the Financial Stress Index

This section briefly describes how we estimate the FSI. We construct all sub-index using monthly data from various sources prior to converting them to a quarterly basis and taking the average values in a quarter, as described in Table 5.

Let $x_{c,t}$ be a vector of length $n_c \times 1$, where $t = 1, \ldots, T^c$, containing financial sub-indexes composing an overall financial index and $h_{c,t} = (g_{c,t}, m_{c,t}, \pi_{c,t})'$, where g_t is the GDP growth in country c, m_t is the growth of $M1$, and π_t is the inflation rate. We assume a TVP-FAVAR with the following form:

$$\begin{aligned} x_{c,t} &= \lambda_{c,t}^y h_{c,t} + \lambda_{c,t}^f f_{c,t} + u_{c,t} \\ \begin{bmatrix} h_{c,t} \\ f_{c,t} \end{bmatrix} &= c_{c,t} + B_{c,t}^1 \begin{bmatrix} h_{c,t-1} \\ f_{c,t-1} \end{bmatrix} + \cdots + B_{c,t}^p \begin{bmatrix} h_{c,t-p} \\ f_{c,t-p} \end{bmatrix} + \varepsilon_{c,t} \end{aligned} \tag{7}$$

where p is the VAR order, $\lambda_{c,t}^y$ and $\lambda_{c,t}^f$ are, respectively, the regression coefficients and factors loading possibility time variant, fci is the unobservable factor interpreted as the financial condition index, $c_{c,t}$ in the intercept and $(B_{c,t}^1, \ldots, B_{c,t}^p)$ are regression coefficients. We assume that $u_{c,t} \sim N(0, V_{c,t})$ and $\varepsilon_{c,t} \sim N(0, Q_{c,t})$, where V_t e Q_t are time varying. The identification is based on the commonly used hypothesis that V_t is a diagonal matrix, such that u_t is a vector of idiosyncratic shocks, and $f_{c,t}$ has all relevant information pertaining to financial variables. For each country, we also assume that the time-varying parameters evolve as random walks of the form:

$$
\begin{aligned}
\lambda_t &= \lambda_{t-1} + \upsilon_t \\
\beta_t &= \beta_{t-1} + \eta_t
\end{aligned}
\tag{8}
$$

where $\lambda = \left((\lambda_t^y)', (\lambda_t^f)'\right)'$, $\beta_t = (c_t', vec(B_t^1)', \ldots, vec(B_t^p)')'$, $\upsilon_t \sim N(0, W_t)$ and $\eta_t \sim N(0, R_t)$, e υ_t. η_t, u_t and ε_t are uncorrelated both in time as well as between equations. We use the same hyperparameter scheme as in Koop and Korobilis (2014).

E Data Appendix

Table 5: Financial Variables

Variables	EMPI: NEER, Reserves			Soverein Spreads				Bank Stress				Stock Market		
Country	Source	Time Span		Measure	Source	Time Span		Measure	Source	Time Span		Source	Time Span	
Argentina	GEM	1994Q1	2015Q4	Embi	GEM	1994Q3	2015Q4	Beta	DataStream	1994Q1	2015Q4	DataStream	1994Q1	2015Q4
Brazil	GEM	1994Q1	2015Q4	Embi	GEM	1994Q3	2015Q4	Beta	DataStream	1994Q4	2015Q4	DataStream	1994Q1	2015Q4
Bulgaria	GEM	1994Q2	2015Q4	Embi	GEM	1994Q2	2014Q1	Beta	DataStream	2001Q1	2015Q4	DataStream	1994Q1	2015Q4
Chile	GEM	1994Q1	2015Q4	Embi	GEM	1999Q3	2015Q4	Beta	DataStream	1994Q1	2015Q4	DataStream	1994Q1	2015Q4
Colombia	GEM	1994Q1	2015Q4	Embi	GEM	1997Q2	2015Q4	B.Spread	IFS	1994Q1	2015Q4	DataStream	1994Q1	2015Q4
Croatia	GEM	1994Q1	2015Q4					B.Spread	IFS	1994Q1	2011Q3	DataStream	1997Q2	2015Q4
Czech Rep.	GEM	1994Q1	2015Q4	S.Spread	IFS	1997Q1	2015Q4	Beta	DataStream	1994Q3	2015Q4	DataStream	1995Q2	2015Q4
Ecuador	GEM	1994Q1	2015Q4	Embi	GEM	1995Q2	2015Q4	B.Spread	IFS	1994Q1	2015Q4			
Hungary	GEM	1994Q1	2015Q4	Embi	GEM	1999Q1	2014Q1	Beta	DataStream	1994Q4	2015Q4	DataStream	1994Q1	2015Q4
India	GEM	1994Q1	2015Q4	Se.Spread	IFS	1994Q2	2015Q4					DataStream	1994Q1	2015Q4
Indonesia	GEM	1994Q1	2015Q4	Embi	GEM	2004Q3	2015Q4	B.Spread	IFS	1994Q1	2015Q4	DataStream	1998Q3	2015Q4
Korea	GEM	1994Q1	2015Q4	Embi	GEM	1994Q3	2014Q1	Beta	DataStream	1994Q1	2015Q4	DataStream	1994Q1	2015Q4
Malaysia	GEM	1994Q1	2015Q4	Embi	GEM	1996a4	2015Q4	Beta	DataStream	1994Q1	2015Q4	DataStream	1994Q1	2015Q4
Mexico	GEM	1994Q1	2015Q4	Embi	GEM	1998Q1	2015Q4	Beta	DataStream	1994Q1	2015Q4	DataStream	1994Q1	2015Q4
Peru	GEM	1994Q1	2015Q4	Embi	GEM	1997Q2	2015Q4	Beta	DataStream	1994Q1	2015Q4	DataStream	1994Q1	2015Q4
Philippines	GEM	1994Q1	2015Q4	Embi	GEM	1998Q1	2015Q4	Beta	DataStream	1994Q1	2015Q4	DataStream	1994Q1	2015Q4
Poland	GEM	1994Q1	2015Q4	Embi	GEM	1995Q4	2014Q1	Beta	DataStream	1994Q3	2015Q4	DataStream	1994Q1	2015Q4
Romania	GEM	1994Q1	2015Q4	S.Spread	IFS	1994Q1	2013Q3	Beta	DataStream	1998Q1	2015Q4	DataStream	1998Q4	2015Q4
Russian F.	GEM	1994Q1	2015Q4	Embi	GEM	1998Q1	2015Q4	Beta	DataStream	1998Q3	2015Q4	DataStream	1998Q4	2015Q4
Slovak Rep.	GEM	1994Q1	2015Q4	Se.Spread	IFS	1998Q3	2015Q4	B.Spread*	IFS/Eurostat	1994Q1	2015Q4	DataStream	1994Q4	2015Q4
Slovenia	GEM	1994Q1	2015Q4	S.Spread	IFS	1996Q1	2007Q2	B.Spread*	IFS/Eurostat	1994Q1	2015Q4	DataStream	1995Q3	2015Q4
South Africa	GEM	1994Q1	2015Q4	Embi	GEM	1995Q1	2015Q4	Beta	DataStream	1994Q1	2015Q4	DataStream	1994Q1	2015Q4
Taiwan	NST	1994Q1	2015Q4	S.Spread	N.Stats.	1994Q1	2015Q4	Beta	DataStream	1994Q1	2015Q4	DataStream	1994Q1	2015Q4
Thailand	GEM	1994Q1	2015Q4	Se.Spread	IFS	1994Q1	2015Q4	Beta	DataStream	1994Q1	2015Q4	DataStream	1994Q1	2015Q4
Turkey	GEM	1994Q1	2015Q4	Embi	GEM	1996Q3	2015Q4	Beta	DataStream	1994Q1	2015Q4	DataStream	1994Q1	2015Q4

Notes: NST stands for National Statistics of Taiwan. B.Spread is the spread between lending and deposit rate. S.Spread is the spread between treasury rate provided by IFS and US Treasury Bill rates, from FRED. Se.Spread is the spread between government securities and US Treasury Bill.

Table 6: National Accounts and Macroeconomic Variables

Country	Var.	Source	Time Span		Var.	Source	Time Span		Var.	Source	Time Span		Var.	Source	Time Span	
Argentina	y	GEM	1994Q1	2015Q2	y (c.p.)	GEM	1994Q1	2015Q2	c, i	IFS	1994Q1	2015Q2	Deflator	GEM	1994Q1	2015Q2
Brazil	y	IBGE	1994Q1	2015Q3	y (c.p.)	IBGE	1994Q1	2015Q3	c, i	IFS	1994Q1	2015Q3	Inflation	GEM	1994Q1	2015Q3
Bulgaria	y	GEM	1995Q1	2015Q4	y (c.p.)	GEM	1995Q1	2015Q4	c, i	IFS	1995Q1	2015Q4	Deflator	GEM	1995Q1	2015Q4
Chile	y	IFS	1996Q1	2015Q4	y (c.p.)	GEM	1996Q1	2015Q4	c, i	IFS	1996Q1	2015Q4	Deflator	GEM	1996Q1	2015Q4
Colombia	y	DANE	1994Q1	2015Q4	y (c.p.)	GEM	1994Q1	2015Q4	c, i	DANE	1994Q1	2015Q4	Deflator	GEM	1994Q1	2015Q4
Croatia	y	IFS	1997Q1	2015Q4	y (c.p.)	IFS	1997Q1	2015Q4	c, i	IFS	1997Q1	2015Q4	Deflator	GEM	1997Q1	2015Q4
Ecuador	y	IFS	1994Q1	2015Q3	y (c.p.)	GEM	1994Q1	2015Q3	c, i	IFS	1994Q1	2015Q3	Inflation	GEM	1994Q1	2015Q3
Hungary	y	GEM	1995Q1	2015Q4	y (c.p.)	GEM	1995Q1	2015Q4	c, i	IFS	1995Q1	2015Q4	Inflation	GEM	1995Q1	2015Q4
India	y	GEM	1996Q2	2015Q4	y (c.p.)	GEM	1996Q2	2015Q4	c, i	OECD	1996Q2	2015Q4	Inflation	GEM	1996Q2	2015Q4
Indonesia	y	GEM	1994Q1	2015Q4	y (c.p.)	GEM	1994Q1	2015Q4	c, i	IFS	1994Q1	2015Q4	Inflation	GEM	1994Q1	2015Q4
Czech Rep.	y	GEM	1996Q1	2015Q4	y (c.p.)	GEM	1996Q1	2015Q3	c, i	OECD	1996Q1	2015Q4	Inflation	GEM	1996Q1	2015Q3
Korea, Rep.	y	GEM	1994Q1	2015Q4	y (c.p.)	GEM	1994Q1	2015Q4	c, i	IFS	1994Q1	2015Q4	Inflation	GEM	1994Q1	2015Q4
Malaysia	y	IFS	1994Q1	2015Q4	y (c.p.)	IFS	1994Q1	2015Q4	c, i	IFS	1994Q1	2015Q4	Inflation	GEM	1994Q1	2015Q4
Mexico	y	GEM	1994Q1	2015Q4	y (c.p.)	GEM	1994Q1	2015Q4	c, i	OECD	1994Q1	2015Q4	Inflation	GEM	1994Q1	2015Q4
Peru	y	BCRP	1994Q1	2015Q4	y (c.p.)	BCRP	1994Q1	2015Q4	c, i	IFS	1994Q1	2015Q4	Inflation	GEM	1994Q1	2015Q4
Philippines	y	GEM	1994Q1	2015Q4	y (c.p.)	GEM	1994Q1	2015Q4	c, i	IFS	1994Q1	2015Q4	Inflation	GEM	1994Q1	2015Q4
Poland	y	GEM	1995Q2	2015Q3	y (c.p.)	GEM	1995Q2	2015Q3	c, i	IFS	1995Q2	2015Q3	Inflation	GEM	1995Q2	2015Q3
Romania	y	GEM	1995Q1	2015Q4	y (c.p.)	GEM	1995Q1	2015Q4	c, i	IFS	1995Q1	2015Q4	Inflation	GEM	1995Q1	2015Q4
Russian F.	y	GEM	1995Q1	2015Q3	y (c.p.)	GEM	1995Q1	2015Q3	c, i	IFS	1995Q1	2015Q3	Inflation	GEM	1995Q1	2015Q3
Slovenia	y	GEM	1995Q1	2015Q4	y (c.p.)	GEM	1995Q1	2015Q4	c, i	OECD	1995Q1	2015Q4	Inflation	GEM	1995Q1	2015Q4
Slovak Rep.	y	GEM	1997Q1	2015Q4	y (c.p.)	GEM	1997Q1	2015Q4	c, i	OECD	1997Q1	2015Q4	Inflation	GEM	1997Q1	2015Q4
South Africa	y	OECD	1994Q1	2015Q4	y (c.p.)	OECD	1994Q1	2015Q4	c, i	OECD	1994Q1	2015Q4	Inflation	GEM	1994Q1	2015Q4
Taiwan	y	GEM	1994Q1	2015Q4	y (c.p.)	GEM	1994Q1	2015Q4	c, i	N.Stat.	1994Q1	2015Q4	Inflation	GEM	1994Q1	2015Q4
Thailand	y	GEM	1994Q1	2015Q4	y (c.p.)	GEM	1994Q1	2015Q4	c, i	IFS	1994Q1	2015Q4	Inflation	GEM	1994Q1	2015Q4
Turkey	y	IFS	1994Q1	2015Q4	y (c.p.)	IFS	1994Q1	2015Q4	c, i	IFS	1994Q1	2015Q4	Inflation	GEM	1994Q1	2015Q4

Notes: GEM: Global Economic Monitor; IBGE: Instituto Brasileiro de Geografia e EstatÃstica; IFS: IMF eLibrary Data; DANE: Departamento Administrativo Nacional de EstadiÃstica; BCRP: Banco Central de Reserva del Peru: OECD: OECD Statistics; N.Stat.: National Statistics Republic of China (Taiwan).

References

Agenor, P.-R., McDermott, C. J., and Prasad, E. S. (2000). Macroeconomic fluctuations in developing countries: some stylized facts. *The World Bank Economic Review*, 14(2):251–285.

Aguiar, M. and Gopinath, G. (2007). Emerging Market Business Cycles: The Cycle Is the Trend. *Journal of Political Economy*, 115(1):69–102.

Akinci, O. (2017). Financial Frictions and Macroeconomic Fluctuations in Emerging Economies. *Working Paper*.

Alessandri, P. and Mumtaz, H. (2013). Financial Conditions and Density Forecasts for US Output and Inflation. *Centre for Central Banking Studies - Joint Research Paper*, (4).

Balakrishnan, R., Danninger, S., Elekdag, S., and Tytell, I. (2011). The Transmission of Financial Stress from Advanced to Emerging Economies. *Emerging Markets Finance and Trade*, 47:40–68.

Bernanke, B., Gertler, M., and Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. *Handbook of macroeconomics*, volume 1.

Bianchi, J. and Mendoza, E. G. (2017). Optimal Time-Consistent Macroprudential Policy. *Journal of Political Economy*, Forthcomin.

Calderón, C. and Fuentes, R. (2010). Characterizing the Business Cycles of Emerging Economies. *World Bank Policy Research Working Paper*, 5343.

Calvo, G. a., Izquierdo, A., and Talvi, E. (2006). Phoenix Miracles in Emerging Markets: Recovering Without Credit From Systemic Financial Crises. *NBER Working Paper Series*, 12101.

Canova, F. and Ciccarelli, M. (2013). Panel Vector Autoregressive Models: A Survey. pages 205–246.

Canova, F. and Dallari, P. (2013). How important is tourism for the international transmission of cyclical fluctuations? Evidence from the Mediterranean. *European Central Bank Working Paper Series*, 1553.

Canova, F. and Pappa, E. (2007). Price Differentials in Monetary Unions: The Role of Fiscal Shocks. *The Economic Journal*, 117(520):713–737.

Cardarelli, R., Elekdag, S., and Lall, S. (2009). Financial Stress, Downturns, and Recoveries. *IMF Working Paper*, WP/09/100.

Chang, R. and Fernández, A. (2013). On the Sources of Aggregate Fluctuations in Emerging Economies. *International Economic Review*, 54(4):1265–1293.

Chen, C. W. S. and Lee, J. C. (1995). Bayesian Inference of Threshold Autoregressive Models. *Journal of Time Series Analysis*, 16(5):483–492.

Ciccarelli, M. and Rebucci, A. (2006). Has the transmission mechanism of European monetary policy changed in the run-up to EMU? *European Economic Review*, 50(3):737–776.

Eichengreen, B., Rose, A., and Wyplosz, C. (2004). Contagious Currency Crises. In *Capital Inflows and Crises*. MIT Press.

Forero, F. P. (2015). Comparing the Transmission of Monetary Policy Shocks in Latin America: A Hierarchical Panel VAR. *Banco Central de Reserva del Perú Working Papers*, 2015-015.

Galvão, A. B. and Owyang, M. T. (2014). Financial Stress Regimes and the Macroeconomy. *Federal Reserve Bank of St. Louis, Working Papers*, 2014(020).

García-Cicco, J., Pancrazi, R., and Uribe, M. (2010). Real Business Cycles in Emerging Countries? *American Economic Review*, 100(5):2510–2531.

Gelman, A. (2006). Prior distributions for variance parameters in hierarchical models. *Bayesian Analysis*, 1(3):515–533.

Gelman, A., Carlin, J., Stern, H., Dunson, D., Vehtari, A., and Rubin, D. (2003). *Bayesian Data Analysis*. Chapman and Hall/CRC, 3 edition edition.

Gilhooly, R., Weale, M. R., and Wieladek, T. (2012). Estimation of Short Dynamic Panels in The Presence of Cross-Sectional Dependence and Dynamic Heterogeneity. *Bank of England Working Paper*, No. 38.

Grant, A. L. and Chan, J. C. (2017). Reconciling output gaps: Unobserved components model and hodrick-prescott filter. *Journal of Economic Dynamics and Control*, 75:114 – 121.

Hatzius, J., Hooper, P., Mishkin, F., Schoenholtz, K. L., and Watson, M. W. (2010). Financial Conditions Indexes : A Fresh Look after the Financial Crisis. *NBER Working Paper*, No. 16150(0340-5761 LA - eng):652–660.

Hsiao, C., Pesaran, M. H., and Tahmiscioglu, A. K. (1999). Bayes Estimation of Short-Run Coefficients in Dynamic Panel Data Models. In Hsiao, C., Lahir, K., Lee, L.-E., and Pesaran, M. H., editors, *Analysis of Panels and Limited Dependent Variables: A Volume in Honour of G. S. Maddala*, pages 268–296. Cambridge University Press.

Jarociński, M. (2010). Responses to monetary policy shocks in the east and the west of Europe: a comparison. *Journal of Applied Econometrics*, 25(5):833–868.

Jeanne, O. and Korinek, A. (2010). Managing Credit Booms and Busts: A Pigouvian Taxation Approach. *NBER Working Papers*.

Kamber, G., Morley, J., and Wong, B. (2018). Intuitive and reliable estimates of the output gap from a beveridge-nelson filter. *Review of Economics and Statistics*, 100(3):550–566.

Kiyotaki, N. and Moore, J. (1997). Credit Cycles. *Journal of Political Economy*, 105(2):211–248.

Koop, G. and Korobilis, D. (2014). A new index of financial conditions. *European Economic Review*, 71:101–116.

Koop, G., Pesaran, M., and Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74(1):119–147.

Lane, P. R. (2003). Business Cycles and Macroeconomic Policy in Emerging Market Economies. *International Finance*, 6(1):89–108.

Lopes, H. F. and West, M. (2004). Bayesian Model Assessment in Factor Analysis. *Statistica Sinica*, 14:41–67.

Mendoza, E. G. (1991). Real Business Cycles in a Small Open Economy. *American Economic Review*, 81(4):797–818.

Mendoza, E. G. (2010). Sudden Stops, Financial Crises, and Leverage. *American Economic Review*, 100(5):1941–1966.

Neumeyer, P. A. and Perri, F. (2005). Business cycles in emerging economies: the role of interest rates. *Journal of Monetary Economics*, 52(2):345–380.

Park, C.-Y. and Mercado, R. V. (2014). Determinants of financial stress in emerging market economies. *Journal of Banking & Finance*, 45:199–224.

Uribe, M. and Schmitt-Grohé, S. (2017). *Open Economy Macroeconomics*. Princeton University Press.