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# Which Global Cycle? A Stochastic Factor Selection Approach for Global Macro-Financial Cycles

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**Abstract:** Instead of assuming a certain factor structure, we statistically test for the factor structure driving common global dynamics in macroeconomic and financial data by employing a stochastic factor selection approach. Using a sample of 16 developed countries from 1996Q1 to 2019Q4, we present strong empirical evidence of a global macro-financial cycle and an independent global financial cycle. Moreover, the global macro-financial cycle we estimate is essentially the global business cycle identified in the literature. It captures the common global macroeconomic dynamics and drives a significant share of the comovement in the financial sector. The remaining commonality in financial variables is driven by separate global financial cycles: the global credit cycle and the global capital flow cycle.

**Keywords:** global macro-financial cycle; global financial cycle; global business cycle; multilevel dynamic factor model; Bayesian; model selection

**JEL Classification:** E44; F44; C52; C32

## 1 Introduction

Both the COVID-19 crisis starting in March 2020 and the great financial crisis of 2007–2009 have reinforced the relevance of studying the linkages and spillovers between economies and their financial systems. The macro-financial perspective analyzes how shocks to financial markets are transmitted to the real economy and vice versa.[1] Furthermore, there exists a large body of empirical evidence of strong global cross-country correlations in economic and financial time series, characterized as global cycles. The literature on the global business cycle (GBCy) is focused on analysing the comovement in macroeconomic aggregates, i.e. GDP, consumption, and investment (see Kose, Otrok, and Whiteman 2003), while the global financial cycle (GFCy) literature studies the common dynamics in asset prices, credit aggregates, and gross capital flows (see Miranda-Agrippino and Rey 2022). The literature typically analyzes these global macroeconomic and financial cycles by assuming the existence of common factors in factor models and largely treated the two global cycles as separate phenomena. Hence, a crucial issue is to explicitly test for the global factor structure and analyze if the domestic interlinkages between the real economy and the financial system persist on the global level, as a common global macro-financial cycle.

1 See Claessens and Kose (2018) for a recent survey.

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In this paper we aim to assess the appropriate global factor structure that captures the common dynamics across the macroeconomic and the financial dimension in a dynamic factor model (DFM). Our approach allows us to assess if the common dynamics are driven by sector-specific cycles, a common global macro-financial cycle, or a combination, without imposing them a priori, explicitly accounting for factor misspecification. Understanding the global macro-financial comovement is important for the coordination of stabilization policies across countries (Obstfeld and Rogoff 2002) as well as to account for systemic risk in the global financial system (Forbes and Warnock 2021). Properly identifying the empirical phenomenon of global cycles enables a more specific discussion on the underlying drivers, for instance assessing the relevance of global risk aversion and US monetary policy as important determinants of such global cycles (Miranda-Agrippino and Rey 2020).

To determine the global factor structure, we adopt a stochastic factor selection approach that statistically tests if particular global factors are relevant model attributes. More specifically, we look at a two-level factor model that features a common global factor in macroeconomic and financial variables, which captures the global macro-financial cycle (GMFCy), and sector-specific factors, capturing the distinct global business and financial cycles. Our approach addresses two central issues in the existing literature that employs factor models to analyze global cycles. First, much of the literature has focused on separate global factors driving fluctuations in macroeconomic variables or financial variables, treating the global macroeconomy and the global financial system separately. This may ignore important macro-financial linkages between the two variable blocks (Ha et al. 2020). Second, in most studies the existence of a particular factor structure is imposed a priori, allowing for possible factor misspecification (Francis, Owyang, and Savascin 2017).

With respect to our modeling choice, the goal is not to analyze spillover effects between the sector-specific cycles[2] but rather to assess if the global comovement, for example, in the financial variables is only due to a global financial cycle or also due to a broader global macro-financial cycle driving the macroeconomic and financial variables jointly. Hence, we adopt the two-level factor model structure that allows for separating the joint dynamics across sectors from the sector-specific commonality. The stochastic factor selection approach provides evidence on which global factors are important in explaining the common dynamics in the data. Furthermore, this focus omits a discussion on the origin of the shocks that drive a potential global macro-financial cycle. We assume the global factors are only driven by their respective factor-specific innovations. This does not imply that a structural financial shock cannot have an impact on macroeconomic variables. Rather, we assume that these effects would be captured by the global macro-financial factor. The commonality across both sectors is captured by the global macro-financial factor. Hence, we do not pursue a full decomposition of common factors into mutually orthogonal common shocks as in Hallin and Liska (2011).[3]

We analyze real GDP growth together with financial variables, i.e. private credit growth and gross capital flows of 16 developed countries using quarterly data from 1996Q1 to 2019Q4. Although data limitations played a role in selecting this time period, it was mainly chosen due to the fact that the period should feature a state of relevant financial globalization. This also warrants the narrow view on the developed economies and their financial system. A separate perspective on cycles specific to the regional or developmental status of different countries, commonly analyzed in the GBCy literature (see Berger, Everaert, and Pozzi 2021; Kose, Otrok, and Whiteman 2003), is not an objective of this study. A priori we expect the sample of developed countries to have the highest probability for common global cycles.

Instead of imposing the existence of the global factors, we follow Berger, Everaert, and Pozzi (2021) who adopted the stochastic model specification search technique of Frühwirth-Schnatter and Wagner (2010) to

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2 An example for this approach is Ha et al. (2020), who model spillovers between the global business and global financial cycle using a VAR structure.

3 Empirical applications of this frequency domain-based approach include studies on the commonality in European industrial production (Hallin and Liska 2011), analysis of market liquidity (Hallin et al. 2011), and a decomposition of the comovement in stock returns and volatilities into global and local shocks (Barigozzi, Hallin, and Soccorsi 2019).

formally test for the factor structure in DFMs.[4] The stochastic model specification search technique of Frühwirth-Schnatter and Wagner (2010) is based on the Bayesian stochastic variable selection method of George and McCulloch (1993).[5] It uses the non-centered reparameterization of state space models that allows to test if the standard deviation of the state error is different from zero. Effectively reducing the factor selection to a variable selection problem.

We provide novel empirical evidence on the factor structure governing global common macroeconomic and financial dynamics. Applying the Bayesian stochastic factor selection approach of Berger, Everaert, and Pozzi (2021), we present strong and robust evidence for a global macro-financial cycle, i.e. a common global factor that significantly drives real GDP growth as well as financial variables such as gross capital flows and credit growth, not previously identified in the literature. Once we include this global macro-financial cycle there is no evidence supporting a separate global macroeconomic factor driving real GDP growth. In fact, the shape of the GMFCy is nearly identical to the GBCy, when estimated from macroeconomic data alone. Hence, we conclude that the global comovement in real GDP growth can be sufficiently characterized by one common global cycle, effectively the global business cycle found in the literature (see Kose, Otrok, and Whiteman 2003). Although the dynamics of the common global cycle is almost purely determined by macroeconomic information, we show it drives significant shares of the variation in financial variables. Furthermore, in contrast to the macroeconomic dimension, after controlling for the common global cycle, our testing procedure detects a separate global financial cycle due to the remaining common dynamics in the financial variables. Hence, the global financial cycle found in gross capital flows and private credit aggregates (Miranda-Agrippino and Rey 2022) is in part driven by the global macro-financial cycle as well as by a pure global financial cycle, i.e. common dynamics that are independent to the global real economy.

The remainder of the paper is structured as follows. Section 2 gives a brief overview on the related literature. The empirical methodology and estimation procedure are introduced in Section 3. Section 4 presents the empirical application, which is followed by a robustness analysis of the results in Section 4.4. Before concluding in Section 6, we discuss our results in relation to the existing literature in Section 5.

## 2 Related Literature

By now there exists a growing but mostly disconnected literature on global business and global financial cycles. Starting with the seminal work of Kose, Otrok, and Whiteman (2003), the literature on global business cycles has focused on estimating global macroeconomic factors that drive fluctuations in economic aggregates across varying time and country samples. Kose, Otrok, and Whiteman (2003) start out by assessing the importance of global, regional, and country-specific factors for dynamics in output, consumption, and investment data. One key finding is that the global business cycle is on average more important for developed countries than their emerging market counterparts. Kose, Otrok, and Whiteman (2008) find an increased influence of the GBCy for the G7 economies during the globalization period (1986–2003) compared to the Bretton Woods period (1960–1972), while Stock and Watson (2005) highlight that the reduced volatility in G7 business cycles is due to weaker common international shocks. Furthermore, Kose, Otrok, and Prasad (2012) present an increased convergence between the business cycles within development-specific groups, i.e. higher comovement within developed countries and within emerging economies but a decoupling of business cycles across groups.

Beginning with the work of Rey (2015), the literature on global financial cycles has focused on different financial dimensions: risky asset prices (Miranda-Agrippino and Rey 2020), house prices (Jackson et al. 2016), and credit and gross capital flows (Barrot and Serven 2018; Davis, Valente, and van Wincoop 2021;

4 This approach is distinct from the literature on the optimal number of factors (e.g. Amengual and Watson 2007; Bai and Ng 2007; Hallin and Liska 2007) or testing for no factor structure in static factor models (Trapani 2018).

5 Examples of empirical work include studies using structural time series model (Frühwirth-Schnatter and Wagner 2010), time-varying parameter models (Chan and Eisenstat 2018; Chan and Strachan 2016), and multilevel dynamic factor models (Berger, Everaert, and Pozzi 2021).

Miranda-Agrippino and Rey 2022). Central issues remain in regard to the overall relevance of the GFCy (Cerutti, Claessens, and Rose 2019) and if there are only separate GFCys for different financial variables or also a joint GFCy across these variables. Ha et al. (2020) find no evidence for a joint GFCy in equity prices, house prices, and long-term interest rates for the G7, while Potjagailo and Wolters (2023) identify both a joint GFCy as well variable-specific GFCys using a time-varying DFM with a data set of 17 developed countries from 1880 to 2013. Furthermore, Davis, Valente, and van Wincoop (2021) and Miranda-Agrippino and Rey (2022) document the close correlation of the global factor in risky asset prices of Miranda-Agrippino and Rey (2020) and the first global factor in gross capital flow data.

In this study however, the focus lies on modelling the common dynamics across the global macroeconomic and financial dimension. Such a possible macro-financial cycle has received significantly less attention. Ha et al. (2020) do not find a GMFCy using macroeconomic and asset price data. Hence, they decide to model macro-financial spillovers using a DFM with a VAR structure. Our approach differs in that we test for the global factor structure and characterize the common dynamics in a two-level factor model. The first level, i.e. the common global factor captures any macro-financial commonality, while the remaining common dynamics that are specific to a certain sector are accounted for by either the macroeconomic or financial factor.

# 3 Testing for Global Factors

We begin by outlining our modeling and estimation approach to test for the common global factors. This includes recasting the two-level dynamic factor model in a form that stochastic factor selection can be applied to and imposing the needed identification restrictions. Importantly, because our approach wants to test if the standard deviation of the factor innovations is different from zero, we require alternative restrictions than usually imposed in the hierarchical factor model literature. The model is then estimated using Bayesian techniques and we briefly describe the prior distributions as well as outline the MCMC algorithm for posterior sampling.

## 3.1 Stochastic Factor Selection in a Two-Level Dynamic Factor Model

### 3.1.1 Centered Parameterization of the DFM

**Observation Equation** In order to model the global dynamics of macroeconomic and financial variables we adopt a two-level dynamic factor model. Intuitively this means that we want to include a global common factor that can influence all time series in the model, i.e. the global macro-financial factor ($G$) on the first level of the hierarchy, and we need sector-specific common factors on the second level, i.e. a global macroeconomic ($S^m$) and a global financial factor ($S^f$) that only load on their respective series. This gives us a factor structure with potentially three global factors.

We have observable variables $y_{it}^k$, with $k \in \{m, f\}$ denoting either macroeconomic ($m$) or financial time series ($f$) for country $i = 1, \dots, N$ at time $t = 1, \dots, T$, assumed to be driven by the global factors and an idiosyncratic component:

$$y_{it}^k = \gamma_i^k G_t + \phi_i^k S_t^k + \mu_{it}^k, \tag{1}$$

with $\gamma_i^k$ and $\phi_i^k$ as the factor loadings and $\mu_{it}^k$ being the idiosyncratic component.

Stacking $y_{it}^k$ over all $k$ and $i$ we get a $(N \times 2) \times 1$ vector $y_t = \left(y_{1t}^m, \dots, y_{Nt}^m, y_{1t}^f, \dots, y_{Nt}^f\right)'$ that allows to re-write the model in matrix form as

$$y_t = \Lambda F_t + \mu_t, \tag{2}$$

with $\mu_t = \left(\mu_{1t}^m, \dots, \mu_{Nt}^m, \mu_{1t}^f, \dots, \mu_{Nt}^f\right)'$ and $F_t = \left(G_t, S_t^m, S_t^f\right)'$ being $J \times 1$ with $J = 3$, equaling the number of factors. $\Lambda = (\Gamma, \Phi)$ is the $(N \times 2) \times J$ loading matrix with $\Gamma = \left(\gamma_{1t}^m, \dots, \gamma_{Nt}^m, \gamma_{1t}^f, \dots, \gamma_{Nt}^f\right)'$, and the sector-factor loading matrix $\Phi$ featuring a block structure, i.e. $\phi_i^m$ is set to zero if $k = f$ and unrestricted otherwise. Consequently we restrict $\phi_i^f = 0$ for $k = m$ and leave it unrestricted otherwise. To add clarity in regard to this two-level structure, the factor loading matrix for the model is

$$\Lambda = \begin{bmatrix} \gamma_{11}^m & \phi_{11}^m & 0 \\ \vdots & \vdots & \vdots \\ \gamma_{N1}^m & \phi_{N1}^m & 0 \\ \gamma_{12}^f & 0 & \phi_{12}^f \\ \vdots & \vdots & \vdots \\ \gamma_{N2}^f & 0 & \phi_{N2}^f \end{bmatrix}$$

**Processes for Factors and Idiosyncratic Components** The dynamics in the unobserved components $F_t$ and $\mu_t$ are assumed to follow zero-mean autoregressive processes,

$$P(L)\,F_t = \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, Q_\varepsilon), \tag{3}$$

$$\Pi(L)\,\mu_t = \nu_t, \quad \nu_t \sim \mathcal{N}(0, \Omega_\nu), \tag{4}$$

where $P(L)$ and $\Pi(L)$ are lag-polynomials of order $p$ and $q$ respectively. The specification allows for no spillovers in the state equation between global factors, i.e. $P_l = \text{diag}\left(\rho_l^G, \rho_l^m, \rho_l^f\right)$ for $l = 1, \ldots, p$. The same holds for the idiosyncratic components, i.e. we assume $\Pi = \text{diag}\left(\pi_{il}^k\right)$ and $\Omega_\nu$ to be a diagonal covariance matrix. The baseline model adopts an AR(1) specification for both the factor and the idiosyncratic component processes. In contrast to much of the literature, $Q_\varepsilon$ is not normalized to the identity matrix, but only restricted to be diagonal, i.e. $\text{diag}\left(\sigma_{\varepsilon^G}^2, \sigma_{\varepsilon^m}^2, \sigma_{\varepsilon^f}^2\right)$ leaving each standard deviation of the factor innovation unconstrained. More on this follows in the identification section below.

### 3.1.2 Identification

One of the key issues in the factor model literature is to separately identify the loadings $\Lambda$ and factors $F_t$ in Eq. (2). We require additional restrictions to avoid observational equivalent models (Bai and Ng 2013). For any non-singular $J \times J$ matrix $H$ we have

$$y_t = (\Lambda H)\left(H^{-1} F_t\right) + \mu_t = \Lambda^* F_t^* + \mu_t. \tag{5}$$

To this end, other studies typically set $Q_\varepsilon$ to the identity matrix for scale identification and restrict one of the loadings for each factor to be strictly positive for sign identification (Kose, Otrok, and Whiteman 2003). However, this setup is not feasible for the present research design. For one, the stochastic factor selection approach adopted wants to test whether the innovation variance of the factors is equal to zero and not impose it. And second, if a factor drops out of the model it is not possible to restrict one of its loadings to be strictly positive.

Given these constraints we follow the identification approach of Berger, Everaert, and Pozzi (2021). First of, we assume uncorrelated factor innovations, i.e. $Q_\varepsilon = \text{diag}\left(\sigma_\varepsilon^2\right)$ with $\sigma_\varepsilon^2 = \left(\sigma_{\varepsilon^G}^2, \sigma_{\varepsilon^m}^2, \sigma_{\varepsilon^f}^2\right)$. Furthermore, we restrict the average of the relevant (non-zero) factor loadings for each factor to be normalized to one.[6]

6 See Berger, Everaert, and Pozzi (2021) for more details.

#### 3.1.3 Non-Centered Parameterization of the DFM

To employ the stochastic model specification search of Frühwirth-Schnatter and Wagner (2010) we need to re-write the DFM using its non-centered parameterization, i.e. we note that $Q_\varepsilon = \Sigma_\varepsilon \Sigma_\varepsilon'$ and divide Eq. (2) by the standard deviation of the state equation innovations. Having $\Sigma_\varepsilon$ now show up in the observation equation allows it to be treated as regression coefficients to which the variable selection technique can be applied to.

The observation equation of the state-space model is re-written as

$$y_t = \Lambda \Sigma_\varepsilon f_t + \mu_t, \tag{6}$$

where $\Sigma_\varepsilon = \operatorname{diag}(\sigma_\varepsilon)$, with $\sigma_\varepsilon = \left(\sigma_{\varepsilon^1}, \sigma_{\varepsilon^2}, \ldots, \sigma_{\varepsilon^J}\right)'$ and $f_{jt} = \frac{F_{jt}}{\sigma_{\varepsilon^j}}$ in $f_t = (f_{1t}, \ldots, f_{Jt})$ are rescaled to have innovations with unit variances.

The non-centered parameterization of the state equations follows to be

$$P(L) f_t = \tilde{\varepsilon}_t, \quad \tilde{\varepsilon}_t \sim \mathcal{N}(0, 1), \tag{7}$$

$$\Pi(L) \mu_t = v_t, \quad v_t \sim \mathcal{N}(0, \Omega_v). \tag{8}$$

A crucial caveat to this non-centered parameterization is the fact that the standardized factors $f_{jt}$ and the corresponding standard deviation $\sigma_{\varepsilon^j}$ are only identified to a sign change (Frühwirth-Schnatter and Wagner 2010). We can multiply $f_{jt}$ and $\sigma_{\varepsilon^j}$ by $-1$ without changing the product. Therefore the likelihood is bimodal with modes $\sigma_{\varepsilon^j}$ and $-\sigma_{\varepsilon^j}$ if $F_{jt}$ exists, i.e. $\sigma^2_{\varepsilon^j} > 0$. If $\sigma^2_{\varepsilon^j} = 0$, then the likelihood is unimodal around zero. Hence, even without the full stochastic factor selection procedure, we can obtain first evidence on the existence of different factors by looking at the posterior distributions of the corresponding standard deviation $\sigma_{\varepsilon^j}$.

#### 3.1.4 Parsimonious DFM

The last step needed for the DFM with stochastic factor selection involves the introduction of binary indicators $\delta_j$ multiplied by each rescaled factor $f_{jt}$. We now have

$$y_t = \Lambda \Sigma_\varepsilon \Delta f_t + \mu_t, \tag{9}$$

where $\Delta = \operatorname{diag}(\delta)$, with $\delta = (\delta_1, \ldots, \delta_J)'$ and for
- $\delta_j = 1$, $f_{jt}$ is included in the model with $\sigma_{\varepsilon^j}$ as unconstrained parameter to be estimated from data.
- $\delta_j = 0$, $f_{jt}$ is excluded from the model with $\sigma_{\varepsilon^j}$ set to zero.

Sampling the binary indicators together with the unknown parameters of the model allows calculating *posterior factor inclusion probabilities* and by combining them we can ultimately obtain *posterior model probabilities*. More specifically, we calculate the marginal likelihoods of the models with and without the respective rescaled factor. After obtaining the posterior probability from combining the marginal likelihoods with the prior, we sample the binary indicator from a Bernoulli distribution. The posterior inclusion probability is then the fraction of draws from the posterior sampler in which the global factor was selected to exist.

## 3.2 Bayesian Estimation

The model requires posterior sampling of the global factors, idiosyncratic components, and estimation of the factor loadings, the autoregressive parameters, factor standard deviations, and the factor inclusion indicators. We adopt a Markov chain Monte Carlo algorithm for posterior inference whose prior distributions and sampling details are outlined in the following.

### 3.2.1 Prior Distributions

To conduct Bayesian estimation of our model, we need to specify prior distributions for the respective parameters. An overview of the assumed prior distributions can be found in Table 1. All regression coefficients have a Gaussian prior distribution. The elements of the loading matrix $\Lambda$ have a prior mean of 1 and the autoregressive parameters $\rho_{jl}$ and $\pi_{il}^k$ a prior mean of 0.5. The prior variance is set equal to $0.15^2$ for both the loadings and the AR parameters. Also following a Gaussian prior are the factor standard deviations $\sigma_{\varepsilon^j} \sim \mathcal{N}(\upsilon_0, V_0)$ with prior mean $\upsilon_0 = 0$ and an uninformative prior variance $V_0 = 10$. Typically in DFMs, the factor innovation variances are modelled using an inverse gamma distribution. However, as shown by Frühwirth-Schnatter and Wagner (2010), $\mathcal{IG}$-distribution with no probability mass at zero pushes the posterior of $\sigma^2_{\varepsilon^j}$ away from zero. Since, we want to test if $\sigma^2_{\varepsilon^j} = 0$ we use the non-centered parameterization to model $\sigma_{\varepsilon^j}$ using a Gaussian prior. The variances of the idiosyncratic innovations $\sigma^2_{\upsilon^{ik}}$ have an inverse gamma distribution with shape $s_0T$ and scale $s_0b_0T$, expressing the prior belief $b_0 = 1$ and strength of the belief $s_0 = 0.1$ as a fraction of the sample size $T$ (see Bauwens, Lubrano, and Richard 2000). Finally, we choose a Bernoulli prior for the binary indicators $\delta_j$. In the baseline case, we set the prior probability of each indicator equaling 1 to 0.5, i.e. $p(\delta = 1) = p_0 = 0.5$. Conscious of the multiplicity control issue in Bayesian variable selection (see Scott and Berger 2010), we add $p_0 = 0.25$ and $p_0 = 0.75$ as robustness checks. Although this should in principle only be a problem in settings with a large number of factors where the prior inclusion probability $p_0 = 0.5$ is likely to lead the fraction of included factors to approach 0.5.

### 3.2.2 Overview of the MCMC Algorithm for Posterior Inference

The posterior density is given by $p(\beta, \delta, f|y)$ where we collect the parameters in $\beta = \left(\lambda, \rho, \phi, \sigma_\varepsilon, \sigma^2_{\upsilon^{ik}}\right)$. Since the joint posterior density does not allow for a closed form solution we employ a Gibbs sampler to sample the binary indicators $\delta$, parameters $\beta$, and factors $f$ conditional on the data.

1. Sample the binary indicators $\delta$ from $p(\delta|y, \beta, f)$ while marginalizing over the parameters $\sigma_\varepsilon$ for which the factor selection is carried out.
2. Sample the parameters $\beta$ from the conditional distribution $p(\beta|y, \delta, f)$
   (a) $\sigma_\varepsilon$ are sampled from $p\left(\sigma_\varepsilon|y, \delta, \lambda, \rho, \pi, \sigma^2_{\upsilon^{ik}}, f\right)$ using Eq. (9) for $f_j$ if $\delta_j = 1$. Otherwise if $\delta_j = 0$, we set the corresponding $\sigma_{\varepsilon^j} = 0$.

**Table 1:** Priors.

| Parameter | Prior distribution | Hyperparameters |
|---|---|---|
| Each factor loading $\lambda$ in $\Lambda$ | $\mathcal{N}(\lambda_0, V_0)$ | $\lambda_0 = 1$<br>$V_0 = 0.15^2$ |
| $\rho_{jl}$ | $\mathcal{N}(\rho_0, V_0)$ | $\rho_0 = 0.5$<br>$V_0 = 0.15^2$ |
| $\pi_{il}^k$ | $\mathcal{N}(\pi_0, V_0)$ | $\pi_0 = 0.5$<br>$V_0 = 0.15^2$ |
| $\sigma_{\varepsilon^j}$ | $\mathcal{N}(\upsilon_0, V_0)$ | $\upsilon_0 = 0$<br>$V_0 = 10$ |
| $\sigma^2_{\upsilon^{ik}}$ | $\mathcal{IG}(s_0T, s_0b_0T)$ | $b_0 = 1$<br>$s_0 = 0.1$ |
| $\delta_j$ | Bernoulli($p_0$) | $p_0 = 0.5$ |

(b) Sample $\lambda$ and $\sigma^2_{\upsilon^{ik}}$ jointly using Eq. (9) and impose identifying normalizations.
(c) Sample AR parameters $\rho$ and $\pi$ from their respective conditionals $p\left(\rho|y, \delta, \lambda, \sigma_\varepsilon, \pi, \sigma^2_{\upsilon^{ik}}, f\right)$ and $p\left(\pi|y, \delta, \lambda, \sigma_\varepsilon, \rho, \sigma^2_{\upsilon^{ik}}, f\right)$. We follow the approach of Chib and Greenberg (1994) by adding a MH-step within the Gibbs sampler.

3. Sample the factors $f$ from $p(f|y, \delta, \beta)$
   (a) We use multi-move sampling (see Carter and Kohn 1994; Kim and Nelson 1998) to sample the included factors.
   (b) Introduce random sign switch on $\sigma_{\varepsilon^j}$ and $f_j$ to make use of the non-identified signs. Specifically, with probability 0.5, $\sigma_{\varepsilon^j}$ and $f_j$ stay the same and with the same probability they are multiplied by −1.
4. Calculate additional quantities, e.g. scaled factors $F_j \equiv \sigma_{\varepsilon^j} f_j$ and variance shares from the variance decomposition.

### 3.2.3 Variance Decomposition

After establishing evidence for the existence of certain common factors, we are interested in assessing the relevance of these factors. A convenient measure is the share of variance of each country's variables explained by the global factors. The variance decomposition of Eq. (1) gives us the variance shares explained by the global macro-financial factor $G_t$ as

$$\theta^G_{ik} = \frac{\mathrm{Var}(\gamma_{ij} G_t)}{\mathrm{Var}\left(y^k_{it}\right)}, \quad \text{with} \quad G_t = \delta_G\, \sigma_{\varepsilon^G}\, g_t,$$

the sector factors $S^k_t$ as

$$\theta^{S^k}_{ik} = \frac{\mathrm{Var}\left(\phi^k_{ij} S^k_{ij}\right)}{\mathrm{Var}\left(y^k_{it}\right)}, \quad \text{with} \quad S^k_t = \delta_k\, \sigma_{\varepsilon^k}\, s^k_t,$$

and the idiosyncratic components as

$$\theta^\mu_{ik} = \frac{\mathrm{Var}\left(\mu^k_{it}\right)}{\mathrm{Var}\left(y^k_{it}\right)}.$$

After obtaining the individual variance shares we calculate the averages across the macroeconomic and financial sector variables to get the average variance shares of the global and sector factors and of the idiosyncratic components.

# 4 Empirical Application

## 4.1 Data

The empirical analysis employs data on real gross domestic product growth, total credit growth and gross capital flows of 16 developed countries from 1996Q1 to 2019Q4.[7] The chosen sample of developed countries emphasizes our aim of focusing on common global cycles in the macroeconomic and financial variables. Next to total credit, our main empirical analysis focuses on gross capital inflows, however the results do not change when using bank loans or gross capital outflows as was checked for robustness in Section 4.4.[8]

7 List of countries and data sources can be found in the Appendix A. The original sample of 20 countries was reduced due to data availability issues.

8 To be clear on the terminology, gross capital inflows are defined as net purchases of domestic assets by foreign investors while gross capital outflows refer to net domestic purchases of foreign assets.

Since the great financial crisis the literature on capital flows has shifted from looking at net flows that capture resource transfers to analyzing gross capital flows which can speak to the overall interlinkage between economies due to cross-border flows of financial assets and liabilities.[9] We focus on aggregate data as we are principally interested in the common dynamics in macroeconomic and financial variables across developed countries. We do not focus on idiosyncratic dynamics of more granular flows, like direct investments or portfolio equity and debt flows that are driven by certain types of investors or financial institutions.

To ensure zero-mean stationary data for our factor analysis, we include demeaned real GDP and demeaned total credit in growth rates. The demeaned gross capital inflows are rescaled by the sum of external assets and liabilities following Davis, Valente, and van Wincoop (2021). More specifically, we take the data on external asset and liability positions from the International Financial Statics (IFS) of the IMF[10] and we define the rescaled country-level capital flows as percentage of the sum of the country's external asset and liability position per period, i.e. $cf_{it} = 100 * \frac{\mathrm{CF}_{it}}{(A+L)_{it}}$, where $\mathrm{CF}_{it}$ are the gross capital flows and $(A + L)_{it}$ the sum of external assets and liabilities for country $i$ in period $t$.

## 4.2 Stochastic Factor Selection Results

### 4.2.1 Descriptive Look at Evidence for Global Factors

We start our main analysis by reminding of the fact that the standardized factors and their respective standard deviations are only identified to a sign change. To make use of this property, the Gibbs sampler includes a random sign switch. Hence, we should see a bimodal posterior distribution for the standard deviation if the corresponding factor exists and an unimodal posterior distribution centered around zero if the factor does not exist. To take a first look at the evidence for the common global cycles we plot the posteriors of factor standard deviations in Figure 1.

For all potential factors we observe bimodality except for the macroeconomic factor in the sample with gross capital flows which is much more unimodal. Especially strong, i.e. with the least probability mass at zero, is the bimodal posterior for the global financial cycle. Regardless of which financial variable is included, the weakest bimodality can be observed for the global business cycle. The posterior standard deviation of $S^m$ extracted from the model with credit growth (top panel in Figure 1) does not display as clear an unimodal density as in the model with gross capital flows (bottom panel) but it still features significant probability mass around zero.

### 4.2.2 Results from Stochastic Factor Selection

For the more rigorous analysis we move beyond merely looking at the posterior distributions of the factor standard deviations. The stochastic factor selection approach tests for the existence of the global factors. The main results of our testing procedure are summarized in Table 2. Given are the posterior factor inclusion probabilities. To control for possible prior sensitivity, we also present the results for the prior inclusion probabilities of $p_0 = 0.25$ and $p_0 = 0.75$, next to the baseline of $p_0 = 0.5$. We observe strong evidence for the global macro-financial and financial factors in the models with credit growth and with capital flows. For all $p_0$, the posterior inclusion probabilities are unity.

For the global macroeconomic factor however, we observe posterior inclusion probabilities well below 50 % across prior specifications and models. In regard to the model with credit growth, the baseline result (i.e. for $p_0 = 0.5$) shows only a 16 % posterior inclusion probability which rises to 37 % for $p_0 = 0.75$. The finding is

9 For example Forbes and Warnock (2012), Broner et al. (2013), Forbes and Warnock (2021), Barrot and Serven (2018).

10 Some countries have missing values for monthly observations. These are interpolated from annual data using the Matlab function `interp1(x,v,xq,'pchip')`.

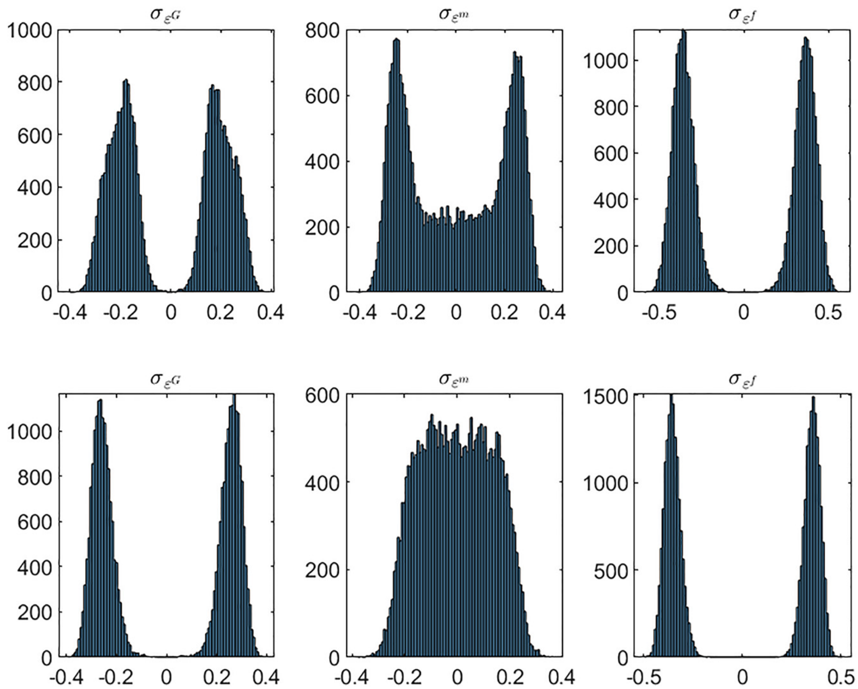


**Figure 1:** Posterior distributions of the global factor standard deviations. Top: sample with credit growth data. Bottom: sample with gross capital flow data. Sample of 30,000 MCMC draws. All binary indicators set to 1.

**Table 2:** Posterior factor inclusion probabilities.

| Prior | Global $G$ | Macro $S^m$ | Financial $S^f$ |
|---|---|---|---|
| | Model with credit growth | | |
| $p_0 = 0.25$ | 1 | 0.11 | 1 |
| $p_0 = 0.5$ | 1 | 0.16 | 1 |
| $p_0 = 0.75$ | 1 | 0.37 | 1 |
| | Model with capital flows | | |
| $p_0 = 0.25$ | 1 | 0.01 | 1 |
| $p_0 = 0.5$ | 1 | 0.04 | 1 |
| $p_0 = 0.75$ | 1 | 0.15 | 1 |

Sample of 30,000 MCMC draws with a burn-in of 3,000 draws where the first 50 % of the burn-in fixed the binary indicators to 1. This burn-in without factor selection follows Frühwirth-Schnatter and Wagner (2010) to ensure reasonable initial values before applying the indicator sampling.

confirmed in the model with capital flows. Here we find an even lower posterior inclusion probability of 4 % for $p_0 = 0.5$ and 15 % for $p_0 = 0.75$.[11]

As laid out in Section 3.1.4 we can use the posterior inclusion probabilities to obtain posterior model probabilities. Table 3 indicates that irrespective of the factor inclusion prior the model with credit growth and the model with capital flows feature only the global macro-financial and the financial factor, i.e. they have the highest posterior probability. The baseline models exclude a separate global business cycle with a probability of

11 Only for very large prior values, i.e. $p_0 > 0.9$, does the posterior inclusion probability cross the threshold of 50 %.

**Table 3:** Posterior model probabilities.

| Global $G$ | Macro $S^m$ | Financial $S^f$ | $p_0 = 0.25$ | $p_0 = 0.5$ | $p_0 = 0.75$ |
|---|---|---|---|---|---|
| Model with credit growth | | | Posterior model probabilities | | |
| 1 | 1 | 1 | 0.13 | 0.16 | 0.37 |
| 1 | 0 | 1 | 0.87 | 0.84 | 0.63 |
| Model with capital flows | | | Posterior model probabilities | | |
| 1 | 1 | 1 | 0.01 | 0.04 | 0.15 |
| 1 | 0 | 1 | 0.99 | 0.96 | 0.85 |

84 % and 96 % for the model with credit and the model with capital flows, respectively. Model specifications that would omit other factors did not receive any posterior probability. Hence, we can draw the first main conclusion from these findings: controlling for a global macro-financial factors eliminates the global macroeconomic factor but not a separate global financial factor.

## 4.3 The Global Cycles Governing Macro-Financial Dynamics

### 4.3.1 The Estimated Global Factors

Selecting the most likely model, we plot the corresponding factor estimates in Figure 2. What we obtain are the global macro-financial cycle and the global financial cycles, i.e. a global credit cycle and a global capital

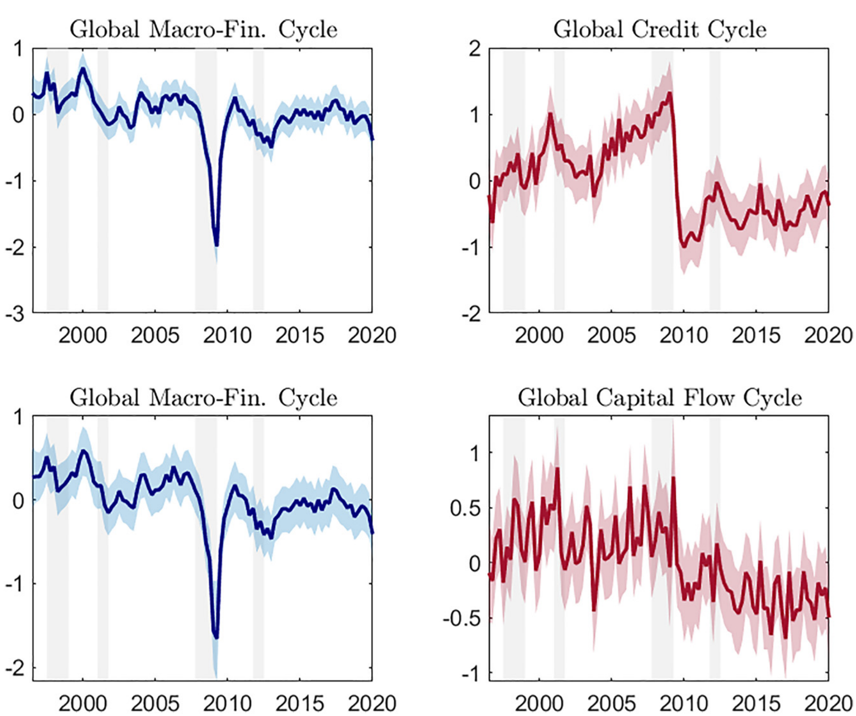


**Figure 2:** Estimates of the selected global factors. Plotted are the factor estimates of the model selected by the SFS approach. The solid lines give mean estimates and the shaded area the 90 % credible sets obtained from 30,000 MCMC draws. Top: Estimates of $G$ and $S^f$ of model with credit growth. Bottom: Estimates of $G$ and $S^f$ of model with gross capital flows.

flow cycle, estimated from models including real GDP growth and credit growth and gross capital flows, respectively. The two estimates of the macro-financial cycle are essentially identical, while the two global financial cycles feature their own dynamics. All cycles feature the strong impact of the great financial crisis of 2007–2009 and to a lesser extend the reaction to the Dotcom crash of 2001 and the *double-dip* due to the Euro area debt crisis.

### 4.3.2 Variance Decomposition

Having established evidence on the existence of the global and the financial factor, we can asses their relevance for the underlying macroeconomic and financial data by looking at the variance decomposition in Table 4. The results for the model specification *SFS-GMF*, i.e. the model preferred by the stochastic factor selection approach, shows that the global factor can explain on average around 11 % of the variance in the macroeconomic time series, regardless of the included financial variable. The financial variables are driven by both the global factor and the financial factor and we find a higher total share of the average explained variance, i.e. 22 % for the model with credit growth and 19 % for the model with capital flows. These results are largely in line with the literature on global cycles.[12] Regardless of the model, the financial factors $S^f$ explain higher shares of the variance on average compared to the global factor $G$. Additionally the GMFCy is found to be more important for capital flows than credit growth. The global factor $G$ explains on average 9 % of the variance in capital flows compared to 6 % for credit growth. Next to these main results of the model Table 4 also includes the variance decomposition for the other possible models, i.e. where we either exclude the global factor or the sector-specific factors. Of

**Table 4:** Variance decomposition for different model specifications.

| **Sector** | **Model spec.** | **Global $G$** | **Sector $S^k$** | **idio. comp.** |
|---|---|---|---|---|
| Model with credit growth: | | | Variance decomposition | |
| Macro | $SFS-GMF$ | 0.11 | 0 | 0.89 |
| | $GMF$ | 0.06 | 0.05 | 0.89 |
| | $G$ | 0.10 | 0 | 0.90 |
| | $MF$ | 0 | 0.10 | 0.90 |
| Financial | $SFS-GMF$ | 0.06 | 0.16 | 0.78 |
| | $GMF$ | 0.03 | 0.15 | 0.82 |
| | $G$ | 0.06 | 0 | 0.94 |
| | $MF$ | 0 | 0.19 | 0.81 |
| Model with capital flows: | | | Variance decomposition | |
| Macro | $SFS-GMF$ | 0.11 | 0 | 0.89 |
| | $GMF$ | 0.10 | 0.02 | 0.89 |
| | $G$ | 0.10 | 0 | 0.90 |
| | $MF$ | 0 | 0.07 | 0.93 |
| Financial | $SFS-GMF$ | 0.09 | 0.10 | 0.81 |
| | $GMF$ | 0.08 | 0.09 | 0.83 |
| | $G$ | 0.10 | 0 | 0.90 |
| | $MF$ | 0 | 0.17 | 0.83 |

SFS-GMF refers to the model selected by the SFS approach, i.e. the model with $G$ and $F$ but no separate macroeconomic factor $M$. The *GMF* model includes all three factors, while the model $G$ and $MF$ only includes the macro-financial factor or the sector-specific factors, respectively.

12 Studies using annual data typically feature larger average variance shares than studies using quarterly data, as higher frequency also implies more idiosyncratic or noisy dynamics in the time series.

interest are especially the results for the macroeconomic data. For the model with only $S^m$, it appears to captures the variance share explained by $G$ in the our baseline model and for the model that includes both $G$ and $S^m$ the variance share seems to be split among the two factors. Hence, the inclusion of one of the factors seems to be sufficient to capture the commonality in global macroeconomic dynamics. This does not hold financial dimension however. The global factor is not able to capture all of the comovement in the financial variables. Furthermore, forcing the model to exclude the global factor, i.e. selecting specification *MF* in Table 4, attributes explanatory power to the global financial cycle that is in fact due to the global macro-financial cycle as it is also significantly driving dynamics in the financial series.

#### 4.3.3 Interpreting the Global Macro-Financial Cycle

A key finding that lets us interpret the nature of the global macro-financial cycle comes from estimating the global cycles $G$ using different financial variables (see Figure 3). While the two global financial cycles (bottom panel) feature their distinct dynamics, we observe that the GMFCys (top panel) estimated with credit growth (dashed line) and gross capital inflow (red line) data are essentially identical. In fact, they are nearly the same as the global business cycle, if estimated using only macroeconomic data (blue line). These results suggest that what we have labelled the global macro-financial cycle is essentially the global business cycle identified in the literature (see Kose, Otrok, and Whiteman 2003). This one common global factor is sufficient to capture the joint macroeconomic dynamics. The inclusion of the financial variables are not important for estimating the shape of the global macro-financial cycle. Nevertheless, we find that the GMFCy explains relevant shares of the variation in both macroeconomic and financial data. Importantly however, as shown in the variance decomposition, the GMFCy does not explain all the comovement in the financial variables of interest. They are additionally driven by a separate global financial cycle.

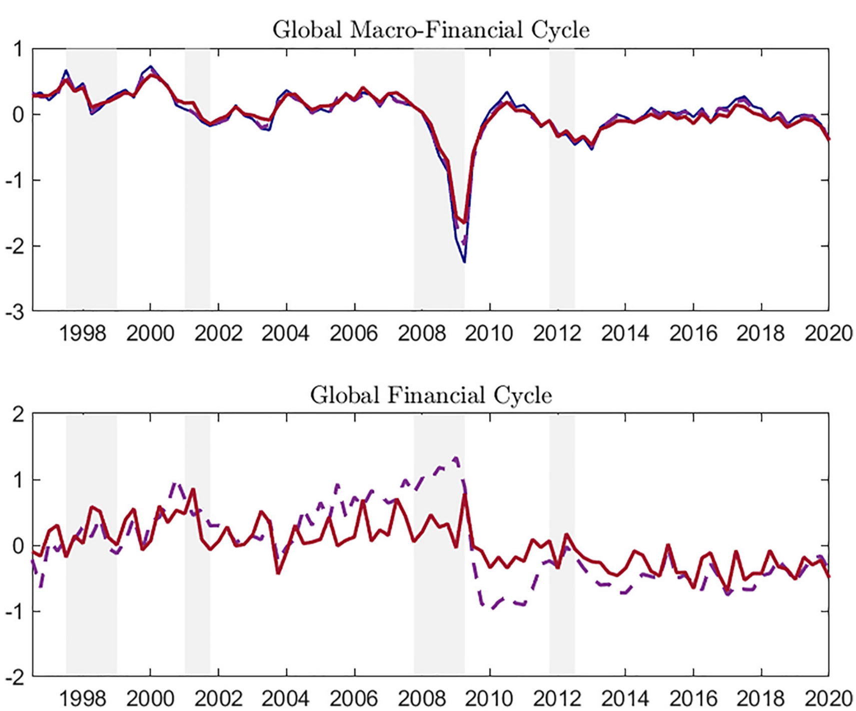


**Figure 3:** Comparison of the different estimates of GMFCy and the unconditional GBCy. Top: $G$ estimated from data set with gross capital flows (red solid line), credit growth (dashed line) and the unconditional global business factor $S^m$ (blue solid line) estimated using only the macroeconomic data set. Bottom: $S^f$ estimated from data set with gross capital flows (red solid line) and credit growth (dashed line).

### 4.4 Robustness

To ensure the robustness of the results we also run the analysis for bank loan growth, capital outflows and hot capital inflows, i.e. we subtract the slower moving, more persistent direct investment flows from the aggregates. These robustness checks confirm the main results.[13] With clear evidence we find a common global macro-financial cycle that explains between 6 % and 11 % of the variation in the underlying time series and an independent global financial cycle that on average accounts for 7 %–13 % of the variation in financial data. The inclusion of an additional global business cycle is not supported by any of the posterior inclusion probabilities for the variables in the robustness analysis.

Since hot inflows lack the more stable direct investment flows, we would expect the comovement to be lower (see Miranda-Agrippino and Rey 2022). A look at the variance decomposition confirms that on average hot capital inflows feature somewhat higher idiosyncratic dynamics.

More important than confirming the factor selection results, we find that regardless of which financial variable is included, the GMFCys and the unconditional GBCy are essentially identical. Hence, adding evidence to our finding that the global macro-financial cycle is essentially the global business cycle (i.e. in regard to shape and dynamics). The separate global financial cycles capture the common dynamics in the financial variables that are independent to the common global cycle determine by the macroeconomic information.

## 5 Discussion

Our stochastic factor selection approach presents us with two distinct global cycles: the global macro-financial cycle and a separate global financial cycle. The GMFCy drives the comovement in global macroeconomic and financial fluctuations. Conditional on the GMFCy, the GFCy features the comovements that are specific to the financial sector. Interestingly, the shape of the GMFCy can be estimated using just the macroeconomic data, i.e. adding financial variables does not add any information on the shape of the common global cycle. This finding relates to recent work on output gap measurement. There is a growing discussion in the literature on domestic business cycles and output gaps in regard to the relevance of financial variables for their measurement and interpretation (see Borio, Disyatatb, and Juselius 2017). For example, Berger, Richter, and Wong (2022) find financial shocks to be important drivers of the US output gap but also show the output gap estimates are largely indifferent to the inclusion of financial information.

Furthermore, we choose a different model structure to characterize the common global dynamics compared to Ha et al. (2020). Both approaches deal with modelling the macro-financial linkages across countries. Ha et al. (2020) do not find evidence for a common factor in a data set comprised of macroeconomic variables and financial asset prices, i.e. stock prices, house prices, and long-term rates. Hence, they model the spillovers between the GBCy and the GFCy using a VAR structure. However, our stochastic factor selection in the model with real GDP growth and financial flow variables, i.e. credit growth and gross capital flows, results in a common global cycle. This indicates that there are relevant common shocks that drive both macroeconomic and financial flow variables.

A key point worth emphasizing here is interpreting our results in light of the literature on global financial cycles. The global factors in risky asset prices (Miranda-Agrippino and Rey 2020) or gross capital flows (Davis, Valente, and van Wincoop 2021) are not estimated from multi-level factor models that are able to distinguish between common shocks to both the macroeconomic and financial dimension and financial shocks that are driving a separate global financial cycle. We show that in fact part of the common variation in financial flow variables is due to a common global factor. Next to this global business cycle capturing real economic conditions that also drive the financial sector, we also find a separate global financial cycle that features shocks unique to global financial conditions. Hence, financial regulation and macroprudential policy could be needed

13 Tables and Figures of the robustness checks can be found in the Appendix B and C.

to specifically address the common global dynamics in financial variables that are independent of real economic conditions.

Some final points on two key limitations of our study are in order. For one, our empirical study is purely reduced-form. We do not take a stance on causal effects or structural drivers of these global cycles. This limits of course our understanding of the underlying shocks driving the common global dynamics. Especially the literature on the GFCy stressed the identification of key drivers, like US monetary policy and global risk aversion (Miranda-Agrippino and Rey 2020). This would be an important area for future research for the GMFCy. The last point relates to the role of the great financial crisis and potential structural breaks. Our sample is to short to estimate pre- and post-crisis models, but further analysis is certainly needed to establish the global cycles' robustness to the great financial crisis and possibly the COVID-19 shock. Although economic and financial integration is still very high for post-GFC developed economies, it could be argued that macroprudential policy and financial regulation might have changed financial dynamics to a degree that the global credit cycle and global capital flow cycles have structurally changed. We see some evidence for this in our factor estimates (see Figure 2), where we can observe a shift in the mean for the global financial factors. A possible threat to our results would be the fact if factors found by our approach only capture the strong global comovement during crisis periods, like the GFC. Essentially only capturing brief crisis-driven strong comovement as opposed to characterizing more general common dynamics of the globalized economies. Though beyond the scope of this paper, explicitly modelling possible structural breaks or time variation in general is an important next step to confirm the robustness of global cycles to events like the global financial crisis and the COVID-19 pandemic.

# 6 Conclusions

We employed a stochastic factor selection approach to study the appropriate global factor structure that characterizes the common global dynamics in macroeconomic and financial series. Our approach explicitly incorporates possible macro-financial linkages by allowing for a common global cycle and avoids imposing a specific global factor structure a priori. Our results are threefold. (1) We find strong evidence in favor of a global macro-financial cycle and a separate global financial cycle. (2) The global macro-financial cycle we estimate is essentially the global business cycle identified in the literature. It captures the common global macroeconomic dynamics and drives part of the comovement in the financial sector. (3) The remaining commonality in financial variables is driven by separate global financial cycles: the global credit cycle and the global capital flow cycle. In summary, we find that common shocks are driving global macro-financial dynamics, while the financial sector is also driven by separate financial shocks that are independent of the common global cycle.

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**Author contributions:** All authors have accepted responsibility for the entire content of this manuscript and approved its submission.

# Appendix A: Data

Tables A.1 and A.2

**Table A.1:** List of countries.

| **Countries:** | | | | | |
|---|---|---|---|---|---|
| Australia | Canada | Germany | Denmark | Spain | Finland |
| France | Great Britain | Italy | Japan | South Korea | Netherlands |
| Norway | New Zealand | Sweden | United States | | |

**Table A.2:** Information on the data sources.

| **Sector** | **Variable** | **Data source** |
|---|---|---|
| Macroeconomic | Real GDP | OECD via DBnomics |
| Financial | Total credit | BIS via DBnomics |
| | Bank loans | BIS via DBnomics |
| | Gross capital flows | IMF BP6, Forbes and Warnock (2021) |
| | Total external assets | IMF BP6 |
| | Total external liabilities | IMF BP6 |

IMF BP6: Balance of Payments and International Investment Position (BP6) data from the International Monetary Fund.

# Appendix B: Tables

See Tables B.1 and B.2

**Table B.1:** Posterior factor inclusion probabilities for samples with different financial variables.

| **Fin. variable** | **Posterior factor inclusion probabilities** | | | |
|---|---|---|---|---|
| | **Prior** | **Global $G$** | **Macro $S^m$** | **Financial $S^f$** |
| Outflows | $p_0 = 0.25$ | 1 | 0.02 | 1 |
| | $p_0 = 0.5$ | 1 | 0.09 | 1 |
| | $p_0 = 0.75$ | 1 | 0.20 | 1 |
| Hot inflows | $p_0 = 0.25$ | 1 | 0.06 | 1 |
| | $p_0 = 0.5$ | 1 | 0.12 | 1 |
| | $p_0 = 0.75$ | 1 | 0.25 | 1 |
| Loans | $p_0 = 0.25$ | 1 | 0.03 | 1 |
| | $p_0 = 0.5$ | 1 | 0.04 | 1 |
| | $p_0 = 0.75$ | 1 | 0.13 | 1 |

**Table B.2:** Variance decomposition for samples with different financial variables.

| Fin. variable | Sector | Model spec. | Variance decomposition | | |
|---|---|---|---|---|---|
| | | | Global $G$ | Sector $S^k$ | idio. comp. |
| Outflows | Macro | $SFS - GMF$ | 0.11 | 0 | 0.89 |
| | Financial | $SFS - GMF$ | 0.09 | 0.09 | 0.82 |
| Hot inflows | Macro | $SFS - GMF$ | 0.11 | 0 | 0.89 |
| | Financial | $SFS - GMF$ | 0.09 | 0.07 | 0.84 |
| Loans | Macro | $SFS - GMF$ | 0.11 | 0 | 0.89 |
| | Financial | $SFS - GMF$ | 0.06 | 0.13 | 0.81 |

$SFS - GMF$ denotes the model selected by the SFS approach using $p_0 = 0.5$.

# Appendix C: Figures

See Figures C.1 and C.2

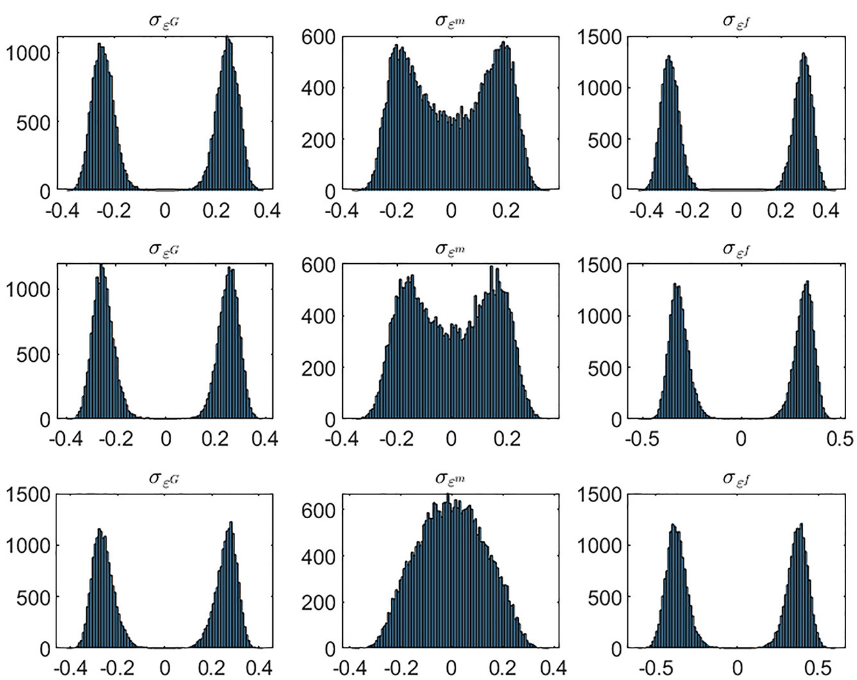


**Figure C.1:** Robustness checks: Posterior distributions of the global factor standard deviations. Top: sample with hot inflow data. Middle: sample with capital outflow data. Bottom: sample with bank loan data. Sample of 30,000 MCMC draws. All binary indicators set to 1.

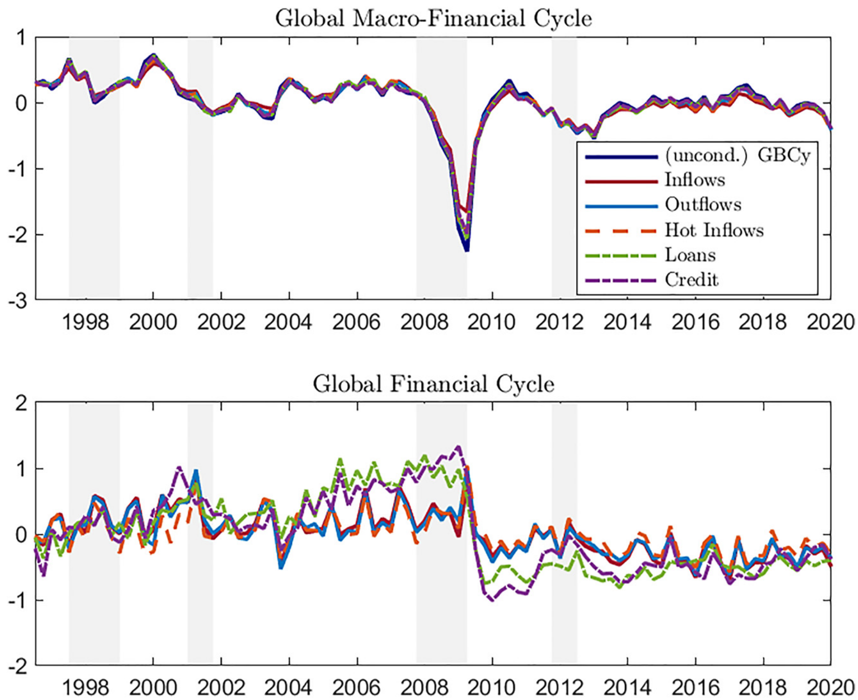


**Figure C.2:** Robustness checks for global factors using different financial variables.

## References


Amengual, D., and M. Watson. 2007. “Consistent Estimation of the Number of Dynamic Factors in a Large N and T Panel.” *Journal of Business & Economic Statistics* 25: 91–6.

Bai, J., and S. Ng. 2007. “Determining the Number of Primitive Shocks in Factor Models.” *Journal of Business & Economic Statistics* 25 (1): 52–60.

Bai, J., and S. Ng. 2013. “Principal Components Estimation and Identification of Static Factors.” *Journal of Econometrics* 176 (1): 18–29.

Barigozzi, M., M. Hallin, and S. Soccorsi. 2019. “Identification of Global and Local Shocks in International Financial Markets via General Dynamic Factor Models.” *Journal of Financial Econometrics* 17 (3): 462–94.

Barrot, L.-D., and L. Serven. 2018. “Gross Capital Flows, Common Factors, and the Global Financial Cycle.” In *Policy Research Working Papers 8354*. The World Bank.

Bauwens, L., M. Lubrano, and J.-F. Richard. 2000. *Bayesian Inference In Dynamic Econometric Models*. Oxford University Press.

Berger, T., G. Everaert, and L. Pozzi. 2021. “Testing for International Business Cycles: A Multilevel Factor Model with Stochastic Factor Selection.” *Journal of Economic Dynamics and Control* 128: 104134.

Berger, T., J. Richter, and B. Wong. 2022. “A Unified Approach for Jointly Estimating the Business and Financial Cycle, and the Role of Financial Factors.” *Journal of Economic Dynamics and Control* 136: 104315.

Borio, C., P. Disyatatb, and M. Juselius. 2017. “Rethinking Potential Output: Embedding Information about the Financial Cycle.” *Oxford Economic Papers* 69 (3): 655–77.

Broner, F., T. Didier, A. Erce, and S. L. Schmukler. 2013. “Gross Capital Flows: Dynamics and Crises.” *Journal of Monetary Economics* 60: 113–33.

Carter, C. K., and R. Kohn. 1994. “On Gibbs Sampling for State Space Models.” *Biometrika* 81 (3): 541–53.

Cerutti, E., S. Claessens, and A. K. Rose. 2019. “How Important is the Global Financial Cycle? Evidence from Capital Flows.” *IMF Economic Review* 67: 24–60.

Chan, J., and E. Eisenstat. 2018. “Comparing Hybrid Time-Varying Parameter Vars.” *Economics Letters* 171: 1–5.

Chan, J., and R. W. Strachan. 2016. “Stochastic Model Specification Search for Time-Varying Parameter Vars.” *Econometric Reviews* 35: 1638–65.

Chib, S., and E. Greenberg. 1994. “Bayes Inference in Regression Models with Arma (p,q) Errors.” *Journal of Econometrics* 64 (1–2): 183–206.

Claessens, S., and M. A. Kose. 2018. “Frontiers of Macrofinancial Linkages.” *BIS Paper* 95 (95).

Davis, S., G. Valente, and E. van Wincoop. 2021. “Global Drivers of Gross and Net Capital Flows.” *Journal of International Economics* 128.
Forbes, K., and F. E. Warnock. 2012. “Capital Flow Waves: Surges, Stops, Flight, and Retrenchment.” *Journal of International Economics* 88: 235−51.
Forbes, K., and F. E. Warnock. 2021. “Capital Flow Waves—Or Ripples? Extreme Capital Flow Movements Since the Crisis.” *Journal of International Money and Finance* 116.
Francis, N., M. T. Owyang, and O. Savascin. 2017. “An Endogenously Clustered Factor Approach to International Business Cycles.” *Journal of Applied Econometrics* 32 (7): 1261−76.
Frühwirth-Schnatter, S., and H. Wagner. 2010. “Stochastic Model Specification Search for Gaussian and Partial Non-Gaussian State Space Models.” *Journal of Econometrics* 154 (1): 85−100.
George, E. I., and R. E. McCulloch. 1993. “Variable Selection via Gibbs Sampling.” *Journal of the American Statistical Association* 88 (423): 881−9.
Ha, J., M. A. Kose, C. Otrok, and E. Prasad. 2020. “Global Macro-Financial Cycles and Spillovers.” In *NBER Working Paper Series 26798*.
Hallin, M., and R. Liska. 2007. “Determining the Number of Factors in the General Dynamic Factor Model.” *Journal of the American Statistical Association* 102: 603−17.
Hallin, M., and R. Liska. 2011. “Dynamic Factors in the Presence of Blocks.” *Journal of Econometrics* 163: 29−41.
Hallin, M., C. Mathias, H. Pirotte, and D. Veredas. 2011. “Market Liquidity as Dynamic Factors.” *Journal of Econometrics* 163: 42−50.
Jackson, E. L., M. Ayhan Kose, C. Otrok, and M. T. Owyang. 2016. “Specification and Estimation of Bayesian Dynamic Factor Models: A Draw Carlo Analysis.” In *Dynamic Factor Models, Advances in Econometrics*.
Kim, C.-J., and C. R. Nelson. 1998. “Business Cycle Turning Points, A New Coincident Index, and Tests of Duration Dependence Based on a Dynamic Factor Model with Regime Switching.” *The Review of Economics and Statistics* 80 (2): 188−201.
Kose, M. A., C. Otrok, and E. Prasad. 2012. “Global Business Cycles: Convergence or Decoupling?” *International Economic Review* 53 (2): 511−38.
Kose, M. A., C. Otrok, and C. H. Whiteman. 2003. “International Business Cycles: World, Region, and Country-Specific Factors.” *The American Economic Review* 93 (4): 1216−39.
Kose, M. A., C. Otrok, and C. H. Whiteman. 2008. “Understanding the Evolution of World Business Cycles.” *Journal of International Economics* 75 (1): 110−30.
Miranda-Agrippino, S., and H. Rey. 2020. “Us Monetary Policy and the Global Financial Cycle.” *The Review of Economic Studies* 87 (6): 2754−76.
Miranda-Agrippino, S., and H. Rey. 2022. “The Global Financial Cycle.” *Handbook of International Economics* 6: 1−43.
Obstfeld, M., and K. Rogoff. 2002. “Global Implications of Self-Oriented National Monetary Rules.” *Quarterly Journal of Economics* 117 (2): 503−35.
Potjagailo, G., and M. H. Wolters. 2023. “Global Financial Cycles since 1880.” *Journal of International Money and Finance* 131.
Rey, H. 2015. “Dilemma Not Trilemma: The Global Financial Cycle and Monetary Policy Independence.” In *NBER Working Paper Series*.
Scott, J. G., and J. O. Berger. 2010. “Bayes and Empirical-Bayes Multiplicity Adjustment in the Variable-Selection Problem.” *Annals of Statistics* 38 (5): 2587−619.
Stock, J. H., and M. W. Watson. 2005. “Understanding Changes in International Business Cycle Dynamics.” *Journal of the European Economic Association* 3 (5): 968−1006.
Trapani. 2018. “A Randomized Sequential Procedure to Determine the Number of Factors.” *Journal of the American Statistical Association* 113 (523): 1341−9.

**Supplementary Material:** This article contains supplementary material (https://doi.org/10.1515/snde-2023-0093).