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Global financial cycles since 1880 ☆

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ABSTRACT

We analyse global aggregate and segment-specific cycles across credit, house prices, equity prices, and interest rates in 17 economies over 130 years using a time-varying dynamic factor model. We show that global financial cycles have gained relevance over time. For equity prices, they now constitute the main driver of fluctuations in most countries. Global cycles in credit and housing have become more pronounced and protracted since the 1980s, and their relevance has increased for a sub-group of financially open and developed economies. Panel regressions show that a country's susceptibility to global financial cycles tends to increase with financial openness and financial integration, the extent of mortgage-related lending, and the efficiency of stock markets. Understanding changes in global co-movement over time and its heterogeneous role across countries matters for the design of financial stabilization policies.

1. Introduction

Today's financial system is global. Banks and investment funds operate across borders and on international bond markets (Kollmann et al., 2011; Kalemli-Ozcan et al., 2013), which has brought many advantages in terms of risk diversification and an efficient flow of funds. However, the 2008 global financial crisis illustrated major risks in terms of boom-bust episodes in credit and financial assets, that can potentially be driven by monetary and financial conditions in one center economy (Rey,

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2015), and that can have severe repercussions to economic activity across many countries (Iacoviello, 2015; Jordà et al., 2015a; Jordà et al., 2015b).

Empirically, an increasing role of global co-movement across credit and financial assets, the "global financial cycle", has been detected (see, e.g., Helbling et al., 2011; Miranda-Agrippino and Rey, 2020). Even though other studies observe a limited quantitative importance of the global financial cycle, little change in its relevance over time, or find asset-specific global cycles instead (Cerutti et al., 2017; International Monetary Fund, 2017; Ha et al., 2017). The mixed picture might relate to two facts. First, most existing studies focus on rather short samples of 25 to 40 years, but credit and house prices are typically found to be long-lasting and to fluctuate slowly (Claessens et al., 2012; Borio, 2014), with boom-bust episodes being rare events. As such, a long sample period can be critical to avoid results being driven by sample specific characteristics. Second, existing studies disagree with regard to the financial aggregates that are relevant measures of global financial cycles: some look at risky equity returns only, or at credit and different asset prices individually, others consider composite indices of financial conditions, and yet others look at capital flows.

In this paper, we provide estimates of the global financial cycle in terms of co-movement across credit, various financial assets, and long-term interest rates across advanced economies over a period of 130 years. The long time span allows us to analyse the properties of recurrent and potentially long-lasting cycles, and to compare large-scale global incidents of financial turmoil, for which even in a long samples only a limited number of observations is available. We estimate the cycles using a time-varying Bayesian dynamic factor model. Shifts in the size of global financial fluctuations and in its impact on individual countries are accounted for in the model via time-varying factor loadings and stochastic volatility. A multi-level factor structure captures global co-movement at different levels: across credit, asset prices, and interest rates (aggregate financial cycle) and specific to each of them (segment-specific cycles). This allows for a comprehensive analysis of co-movement that can occur both across financial aggregates or within segments, and whose relative importance might vary over time. The joint measurement of these different cycles leads us to detect an increasing role of global dynamics that occurs at different cyclical frequencies.

We investigate three questions. First, what are the main characteristics of global financial cycles and how do cyclical properties evolve? We find evidence for an aggregate global financial cycle and additional segment-specific cycles occurring at different cycle lengths. The aggregate cycle captures joint co-movement between credit, asset prices and long-term interest rates and operates at business cycle frequencies. For the period from 1990 to 2012, the global financial cycle closely compares to the global financial factor estimated by Miranda-Agrippino and Rey (2020), notwithstanding the much lower number of series used in the extraction of our factor. Segment-specific cycles capture additional cross-country co-movement in each of the financial aggregates, conditionally on the aggregate financial cycle. We observe long-lasting cycles in credit and house prices, in line with those typically targeted by macro-prudential policy (see, e.g., Borio, 2014). However, we also detect short-lived cycles in equity prices that can reflect more volatile global financial spillovers.

Second, how relevant are global financial cycles for explaining fluctuations in the data over time? We find them to have been present throughout the sample period, explaining substantial shares of fluctuations in financial aggregates. But the relevance of global financial cycles has increased and their characteristics have evolved over time. The role of the global equity cycle has increased steadily and strongly for all countries in the sample, so that by the end of the sample more than half of equity price fluctuations are due to global dynamics. Additionally, global cycles in credit and house prices have become more protracted and ample over the last decades. The susceptibility of credit and house prices to global dynamics has increased in the UK, the US and in Nordic European countries, but remained constant or slightly declined in continental Europe and other advanced economies.

Third, is the heterogeneous role that global financial cycles play for individual countries related to the degree of financial development and integration? We exploit the fact that our model provides variance shares that are explained by the global financial cycle for each year and country, and we link them with country characteristics via panel regressions. We find that a country's financial susceptibility to global forces increases with the degree of financial openness. Credit and house prices in countries that are more financially developed in terms of a higher stock market depth and efficiency, and that have stronger linkages between credit and mortgage markets are more susceptible to global dynamics.

These findings carry various policy implications for the monitoring of global financial risks and for the design and cross-country coordination of macroprudential policies. The co-existence of an aggregate global financial cycle and segment-specific cycles with different cyclical behaviour over time suggests that composite global financial indices and individual financial series can signal different types of financial risks. This matters in the context of GDP-at-risk, a metric of GDP tail risk monitored by institutions and central banks. Adrian et al. (2019) document that financial conditions, measured by a domestic composite index, create downside risk for the economy through their role for the lower quantile of GDP growth. Our findings indicate that additional risks operating at a lower frequency might relate to global credit conditions, in line with results by Lloyd et al. (2021), and that there can also be risks from more volatile global equity price fluctuations. Further, our finding of financial cycles changing over time and occurring at different cycle lengths implies that a flexible toolkit of policy instruments might be required. This could include a combination of regular macroprudential measures aiming at the stabilization of slower-moving credit and house price cycles (Borio et al., 2019), and occasional monetary policy interventions aiming at the stabilization of more sudden and pronounced global fluctuations in asset prices and exchange rates, such as those that occurred at the onset of the COVID-19 pandemic (Jiang et al., 2021; Cesa-Bianchi et al., 2022; Goldberg and Ravazzolo, 2022). Finally, our result on the role of country characteristics suggest that heterogeneity in the degree of financial development is important when thinking about the coordination of financial stabilization policies across countries and sectors, and for preventing financial imbalances in one economy from spreading globally (Rajan, 2015; Cecchetti and Tucker, (2016, January).; Gopinath, 2017).

Our analysis relates to various existing studies that look at the cyclical properties according to which financial aggregates fluctuate, mostly focusing on domestic rather than global cycles. These papers observe a financial cycle length of 15 to 20 years and a large amplitude of fluctuations for recent sample periods, where the (domestic) financial cycle is defined in terms of credit and house prices (Claessens et al., 2012; Borio, 2014; Rünstler and Vlekke, 2018; Lang and Welz, 2018). Our findings confirm such a cycle length for the global and house price cycles, but only for the period of the last forty years. The long sample period uncovers that the properties of these cycles changed over time: they have become more prolonged and ample, whereas they were more erratic and short-lived before, including during the early era of financial globalisation in the early 20th century.

Various studies have looked at global financial co-movement, again mostly considering relatively short periods. These studies either focus on co-movement in slow-moving variables such as credit or house prices only (Helbling et al., 2011; Hirata et al., 2012), or on risky equity returns (Miranda-Agrippino and Rey, 2020), or capital flows (Cerutti et al., 2017). Ha et al. (2017) allow for asset-specific as well as aggregate global cycles, finding evidence for the former. A few recent studies have also analysed global financial co-movement using long data sets also covering over 100 years, but they differ from our approach in terms of variables covered and methodology. Jordà et al. (2019) analyse global asset-specific co-movement and Meller and Metiu (2017) global co-movement of credit, using average bilateral cross-country correlations, respectively. Bekaert and Mehl (2019) look at global co-movement of equity returns within a factor model, finding a "swoosh" pattern in the role of global dynamics. Del Negro et al. (2019) look at global trends, rather than cyclical fluctuations, in interest rates using a vector autoregression (VAR), and find a common decline in interest rate trends. We confirm the finding of a stronger role of global financial cycles for equity prices over time (Miranda-Agrippino and Rey, 2020; Jordà et al., 2019). But for credit and house price cycles, we detect cross-country heterogeneity in the susceptibility to global cycles that relates to the degree of a country's financial development.

The remainder of the paper is organised as follows. Section 2 presents the historical data set. Section 3 describes the time-varying dynamic factor model with a multi-level factor structure. Section 4 presents the results, and Section 5 concludes.

2. Data and data quality

We use annual data on GDP, credit, house prices, equity prices, and long-term interest rates from 1880 to 2013. The data are taken from the Jordà-Schularick-Taylor Macrohistory Database.[1] We include data for 17 advanced economies for each of these variables, except for house prices where longer data series are available for 14 countries only.[2] These economies cover more than 50% of world GDP on average over the sample period. Nominal series are deflated by CPI. We take logs of all time series except of interest rates, and we take first differences of all series. Since the log-differenced series show long-run trends, we compute deviations from centred moving averages of $\pm$ 8 years similar to Stock and Watson (2012).[3]

The historical data face quality limitations that can pose challenges for the estimation and interpretation of results. First, our sample period includes the two World Wars. During these and the first years after the wars, data points are missing and available data show strong fluctuations. These reflect the extreme economic environment of war, but also the fact that a precise collection of statistical data was most likely not a priority for many countries during the wars. At the same time, such large short-run fluctuations are very hard to grasp econometrically and might distort the results, including for other periods that we are primarily interested in, such as the "first era of financial globalization" prior to World War I (Schularick and Taylor, 2012; Reinhart et al., 2016), the Great Depression and the post-war period. Therefore, we opt for excluding the war periods from our analysis. We do so by setting all observations for the years 1914 to 1922 and 1939 to 1947 to missing values, which leaves 116 usable years in our sample. In addition, we identify a few remaining outliers in line with the approach by Stock and Watson (2005), and we also replace them by missing values. While the model samples missing observations based on the Kalman filter, we refrain from analysing these estimates due to the high uncertainty associated with estimates of missing observations around the two world wars.

Second, apart from the observations that we set to be unknown manually, the financial variables from the Macrohistory database show missing values for some countries and periods, mostly at the beginning of the sample.[4] About 85 percent of all missing values are clustered at the beginning of the sample between 1880 and 1913. More than 10 percent of credit observations and almost 30 percent of house price and equity price observations, respectively, are missing during this sub-period. This

[1] The data set is based on a broad range of historical sources and publications of statistical offices and central banks (Jordà et al., 2017). For details regarding the data sources and the construction of the data series, we refer to the online appendix published on www.macrohistory.net.

[2] These are Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States. House prices are not included for Spain, Italy and Portugal since they are only available from the 1970s or later. When including these series results remain similar, but estimation is less stable due to a high number of missing values.

[3] Results remain similar when applying the Christiano-Fitzgerald (CF) bandpass filter (window of 2 to 32 years) or the Baxter-King filter (filter lag length K = 10). The moving average approach has the advantage of easier handling of missing values, which are sampled after transformation via the Gibbs sampler.

[4] Summary statistics regarding the total number of observations and the number of missing values for each of the financial variables are shown in the online appendix.

substantial share of missing data during the early part of the sample implies that we can be less confident about what we can learn from the data on global financial co-movement during this period. [5]

Third, descriptive statistics over sub-periods shown in the online appendix reveal sizeable changes over time in the level and the volatility of the standardised transformed series. The means show pronounced drops during the period covering the 1929 stock market crash and the Great Depression in the 1930s. Equity prices and GDP growth also drop during the sub-sample that covers the 2008 financial crisis. The volatility of most series increases initially during early sub-samples, and then declines over the post-war period, with the exception of equity prices where volatility is largest in the most recent sub sample.

These changing time series properties and evolution of data quality underline the need for a flexible model that accounts for missing values and that captures variation in the volatility in the data. Within the Bayesian estimation approach, missing data points are handled within the Kalman filter. In addition, the time-varying parameters can capture changes in the volatility of individual time series (stochastic volatilities in idiosyncratic components) or across many series (stochastic volatilities of factors) that stem not only from structural economic changes, but also from changes in data quality.

3. Methodology

We estimate a dynamic factor model (DFM) following the methodology developed in Del Negro and Otrok (2008) and applied in Ritschl et al. (2016). The multi-level factor structure discussed in Section 3.2 accounts for co-movement at different levels of aggregation. The model addresses time-variation via time-varying loadings and stochastic volatility, pinned down by priors discussed in Section 3.3.

3.1. Time-varying parameter DFM

The dynamic factor model describes a panel of time series as a function of a small set of dynamic factors and dynamic idiosyncratic components specific to each time series via the observation equation:

$$Y_t = \Lambda_t F_t + U_t, \tag{1}$$

where Λ_t is a $n \times k$ matrix of time-dependent loadings which relate the n time series Y_t to the K common factors $F_t = [f_{1,t}, \ldots, f_{K,t}]$ for $t = 1, \ldots, T$ and $U_t = [u_{1,t}, \ldots, u_{n,t}]$ are the idiosyncratic components. The factors and idiosyncratic components follow autoregressive processes of order q and p, respectively:

$$F_t = \Phi F_{t-1} + e^{H_t^f} \xi_t, \tag{2}$$

$$U_t = \Theta U_{t-1} + e^{H_t^u} \chi_t, \tag{3}$$

where Φ and Θ are block-diagonal polynomials of order q and p, respectively, and $\xi_t \sim N(0_{K\times 1}, I_{K\times K})$ and $\chi_t \sim N(0_{n\times 1}, I_{n\times n})$. The factors represent unobserved components which affect all time series jointly. They are assumed to be orthogonal to each other and not to affect each other at lags.[6] The idiosyncratic components are assumed to be independent across time series so that all co-movement in the data is captured by the common factors. For the lag length we choose $q = 8$ and $p = 1$ following Ritschl et al. (2016).[7]

The log volatilities of the K factors and of the n idiosyncratic components follow driftless random walks:

$$H_t = H_{t-1} + \eta_t, \tag{4}$$

where H_t are the $K + n$ log volatilities with $\eta_t \sim N(0_{(K+n)\times 1}, \Omega_\eta)$ and $\Omega_\eta = diag(\sigma^2_{\eta 1}, \ldots, \sigma^2_{\eta K}, \sigma^2_{\eta K+1}, \ldots, \sigma^2_{\eta K+n})$. The variances $\sigma^2_{\eta 1}, \ldots, \sigma^2_{\eta K}$ correspond to the volatilities of factors, and $\sigma^2_{\eta K+1}, \ldots, \sigma^2_{\eta K+n}$ correspond to the volatilities of idiosyncratic components, and all volatilities are assumed to be independent from each other. Also the $n \times K$ factor loadings are assumed to follow driftless random walks:

$$\Lambda_t = \Lambda_{t-1} + \epsilon_t, \tag{5}$$

[5] During the first part of the sample, the Macrohistory database mostly relies on national sources for financial data, and for many series sources change over time (Jordà et al., 2017). For the post-war period, international sources such as the IMF or the OECD are used much more broadly. For house price series data issues might be particularly relevant since during the early period many sources refer to urban (instead of nationwide) prices and measurement approaches differ across sources (e.g. sale prices in the market, listing prices, appraised values, see Knoll et al. (2017)).

[6] This is a typical assumption in the literature, see for instance Banbura et al. (2013) and Miranda-Agrippino and Rey (2020), and it significantly reduces the number of parameters to be estimated compared to a model with unrestricted spillover effects across factors. The identification of factors is not affected by restricting the spillovers among them to zero.

[7] The number of lags of the idiosyncratic components process is kept small in order to perform quasi-differencing in a straightforward manner, as it is typically done in the literature (Del Negro and Otrok, 2008; Miranda-Agrippino and Rey, 2020; Ha et al., 2017).

where $\epsilon_t \sim N(0_{n\times K}, \Omega_\epsilon)$ and $\Omega_\epsilon = diag(\sigma^2_{\epsilon 1}, \dots, \sigma^2_{\epsilon(n\times K)})$. The loadings are independent across time-series. This is an identifying assumption: while both factors and loadings vary over time, only factors capture the dynamics in the co-movement among the series.

Additional identification restrictions are required to resolve indeterminacy in the dynamic factor model. On the one hand, the relative scale of the factors and loadings is indeterminate, because the likelihood stays the same if we multiply the loadings by a factor a and divide the factors by a, while adjusting their log volatility accordingly. We address the scale indeterminacy by fixing the initial values of the log volatilities to $h_{j,0} = 0$, following Del Negro and Otrok (2008). On the other hand, the sign of the factors and the loadings is indeterminate, because the likelihood stays the same if we multiply both by -1. We address the sign indeterminacy by restricting the signs of one of the loadings of each factor to be positive. In particular, for each factor, we restrict the variable which exhibits the highest correlation with the starting value of the factor, and whose loadings are not restricted to zero due to the multi-level factor structure, to load positively on that factor.

3.2. Multi-level factor structure

To consider global co-movement with regard to four financial series and GDP growth, we require a factor model which accounts for potential common dynamics between different financial aggregates, and for each aggregate across countries. For this purpose, we apply a multi-level structure to the loadings matrix of the dynamic factor model, as in Kose et al. (2003, 2012),Breitung (2016) and Ha et al. (2017).

We first define a global financial factor which captures common shocks driving all financial variables across all countries in the data set. Then, for each variable we include a variable-specific factor that captures co-movement across countries specific to the respective variable.[8] The observation equation for the multi-level model reads as follows:

$$\begin{bmatrix} Y_t^{fin_1} \\ \vdots \\ Y_t^{fin_r} \\ Y_t^{gdp} \end{bmatrix} = \begin{bmatrix} \Lambda_t^{fin_1 F} & \Lambda_t^{fin_1} & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & & \\ \Lambda_t^{fin_r F} & 0 & \dots & \Lambda_t^{fin_r} & 0 \\ 0 & 0 & \dots & 0 & \Lambda_t^{gdp} \end{bmatrix} \begin{bmatrix} f_t^F \\ f_t^{fin_1} \\ \vdots \\ f_t^{fin_r} \\ f_t^{gdp} \end{bmatrix} + \begin{bmatrix} U_t^{fin_1} \\ \vdots \\ U_t^{fin_r} \\ U_t^{gdp} \end{bmatrix}, \tag{6}$$

where Y_t^{gdp} are the GDP growth series and $Y_t^{fin_1}, \dots, Y_t^{fin_r}$ are the $r = 4$ financial series included in the model, over N countries, respectively. All financial time series, but not GDP, can a priori be driven by the financial factor f_t^F. In addition, the time series for each variable depend on their corresponding variable-specific factor, f_t^{gdp} or $f_t^{fin_1}, \dots, f_t^{fin_r}$, but not on the other variable-specific factors. U_t^{gdp} and $U_t^{fin_1}, \dots, U_t^{fin_r}$ are the idiosyncratic components of each variable over N countries, respectively. The factors and idiosyncratic components evolve as autoregressive processes with stochastic volatilities, as specified in Eqs. (2)–(4), the loadings evolve as random walks as specified in Eq. (5).

3.3. Priors

The priors for the variances corresponding to the law of motion of the loadings $(\sigma^2_{\epsilon 1}, \dots, \sigma^2_{\epsilon n})$ and those for the stochastic volatilities of the factors and idiosyncratic components $(\sigma^2_{\eta 1}, \dots, \sigma^2_{\eta K}, \sigma^2_{\eta K+1}, \dots, \sigma^2_{\eta K+n})$ pin down the amount of variation over time in the parameters. The variances are assumed to follow Inverse-Gamma distributions

$$\sigma^2_{\epsilon_i} \sim IG(v_\epsilon, s^2_\epsilon),$$

$$\sigma^2_{\eta_j} \sim IG(v_\eta, s^2_\eta),$$

for $i = 1, \dots, n.$ and for $j = 1, \dots, K, K+1, \dots, K+n$. The scale hyperparameters s^2 represent beliefs regarding the amount of variation in the innovations, and the degrees of freedom hyperparameters v represent the strengths of these beliefs.

We choose the priors based on the belief that fluctuations over time in the loadings and stochastic volatilities are limited to gradual, long-term changes. As such, the parameters reflect structural and institutional changes that impact the degree of global financial integration, as opposed to short-term global cyclical fluctuations that are captured by the factors. At the same time, we incorporate the belief that smooth changes in the susceptibility of financial series to global shocks may have been relatively pronounced, due to developments specific to that variable or country. We therefore choose the priors such that variation in the loadings is favored over variation in the stochastic volatilities by setting the scale parameter for the vari-

[8] Studies focusing on business cycle co-movement among large numbers of countries have identified regional dynamics, with a convergence within advanced economies and a decoupling from emerging market dynamics (Kose et al., 2003; Kose et al., 2012; Carstensen and Salzmann, 2017; Berger and Richter, 2017). Since we focus on advanced economies, we expect regional decoupling to be limited and do not include regional factors. Further, defining country groupings is not obvious over the long sample. The integration among euro area countries occurred in the second half of the sample. Before that, integration might have been stronger with the UK, which had close links to Australia and Canada via the British Empire and Commonwealth.

ance of the former to be relatively larger.[9] In particular, we set $s^2_\epsilon = 0.1$ for the scale of the loadings and $s^2_\eta = 0.025$ for the scales of all stochastic volatilities, and we set all the degrees of freedom parameters to $v_\epsilon = v_\eta = 134 = T$.

For the autoregressive coefficients, we specify shrinkage priors which punish more distant lags. The prior for the AR-coefficients of the factor equation $\phi_1, \ldots, \phi_q$ is.

$\phi_{prior} \sim N(0_{q\times 1}, \underline{V_\phi})$, where $\underline{V_\phi} = \tau_1 diag(1, \frac{1}{2}, \ldots, \frac{1}{q})$ and $\tau_1 = 0.2$. The prior for the AR-coefficients of the idiosyncratic components $\theta_{i,1}, \ldots, \theta_{i,p}$ is

$\theta_{prior} \sim N(0_{p\times 1}, \underline{V_\theta})$, where $\underline{V_\theta} = \tau_2 diag(1, \frac{1}{2}, \ldots, \frac{1}{p})$ and $\tau_2 = 1$.

3.4. Estimation

We estimate the model using the Gibbs sampler. We sequentially draw from four blocks of standard conditional distributions to obtain an empirical approximation of the joint distribution of parameters and state variables. In the first block, we sample the time-varying factor loadings conditionally on the factors, stochastic volatilities and time invariant parameters using Carter and Kohn's algorithm. In the second block, we sample the factors conditionally on the loadings matrix with zero restrictions, the stochastic volatilities and the time invariant parameters as in Carter and Kohn (1994). We sample missing values within Carter and Kohn's algorithm. For the World War years, for which all series are taken as unobserved, we skip the updating step in the Kalman filter. For other missing values, where only some of the series are missing in a given year, we set the respective data point equal to zero and attach a very high variance to it. In the third block, we sample the stochastic volatilities conditionally on the other state variables and on the parameters, as in Kim et al. (1998). In the fourth block, we estimate time invariant parameters via Maximum Likelihood, conditionally on the factors, loadings and stochastic volatilities.[10]

We use principal component estimates as starting values for the factors and loadings. We run the sampler for 20,000 draws. We discard the first 80% (16,000) as burn-in and we save every eighth draw to limit autocorrelation of the draws, which yields 500 draws used for inference. We check the convergence of the Gibbs sampler via visual inspection of the parameter and state variable draws, and by calculating the recursive means and variances of draws, which gave satisfactory results.[11]

4. Results

In the following, we provide answers to the question of how global financial cycles look, how their relevance for individual countries has changed over time, and we use panel regressions to check how differences in the susceptibility to global factors across countries and over time relate to country characteristics.

4.1. Global financial cycles

Fig. 1 shows the medians from the posteriors of the six factors measuring global cycles, together with 68 percent credible sets. The global factors are overall estimated precisely, although the credible sets are wider where there are relatively many missing values, such as in the early part of the sample and for the house price factor. Throughout the sample period, there is significant cyclical global co-movement jointly between credit and various asset prices, captured by the financial factor (upper-left sub-plot). From 1990 onward, it compares remarkably well to the global financial factor by Miranda-Agrippino and Rey (2020) which they estimate from a much wider set of more than 850 monthly series of asset, bond and commodity prices, as illustrated in the online appendix.

Conditionally on the aggregate financial factor, there is substantial variable-specific global co-movement for individual financial segments, i.e. credit, house prices and equity prices. Co-movement in credit is pronounced during the inter-war period, but rather flat during the 1960s, reflecting tight capital controls during the Bretton-Woods era. For the period since the 1980s, we observe a clear synchronised increase in the length and amplitude of the global credit and house price cycles.[12] This might reflect the rise of personal financial services and the increased demand for commercial estate, driven by financial liberalization policies around that time (Ball, 1994). The global credit factor compares quite closely to HP-filtered credit-to-GDP measures by the Bank of International Settlements for various countries, as illustrated in the online appendix. The global equity price factor shows volatile cycles and reflects major stock market busts such as those during the 1970s. The global equity

[9] Del Negro and Otrok (2008) follow a similar approach when estimating global business cycles between 1970 and 2005, in order to achieve smooth variation not only in the volatilities, but also in the loadings.

[10] We eliminate the idiosyncratic terms from the state vector, so that its dimension does not increase with n, via quasi-differencing Eq. (1), as in Quah et al. (1993) and Del Negro and Otrok (2008). In order to estimate the autoregressive coefficients in Eq. (3) via maximum likelihood, we need a series of error terms U_t without missing values. This is achieved by sampling the idiosyncratic components conditional on the state variables and time-invariant parameters using Carter and Kohn's algorithm. For this purpose, we define a state space model with the measurement equation $y_{i,t} = \kappa_{i,t} + u_{i,t}$, where $\kappa_{i,t} = \lambda_t f_t$ is a time-varying constant, and $u_{i,t}$ is the state variable.

[11] Recursive means and variances of Gibbs draws for selected state variables are shown in the online appendix.

[12] Results for a specification with a joint credit-house price factor instead of a separate credit and a house price factor are similar and are shown in the online appendix. Findings are also robust when we include house price series for Italy, Spain and Portugal.

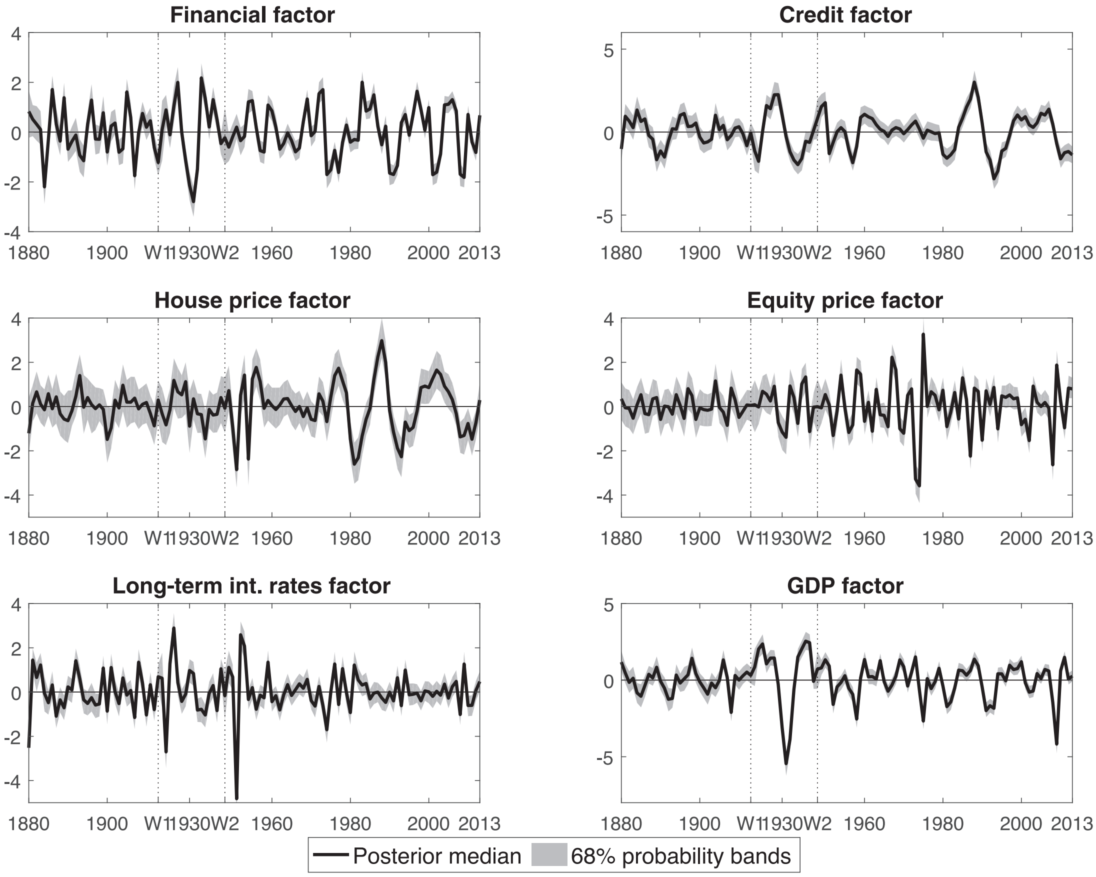

Fig. 1. Global Factors Notes: The financial factor represents common dynamics across all financial variables and countries. The remaining factors represent common variable-specific dynamics across countries. Solid lines show the posterior median, gray areas show the 68 percent credible sets. Data for the years 1914 to 1922, 1939 to 1947 are set to missing values and not used to update the posterior, the factors are thus not plotted over these periods (indicated by dotted vertical lines).

price factor operates at a higher frequency and reflects the stock market turbulence around the end of the 1980s and beginning of the 1990s, the 2001 burst of the dot-com bubble, and the dynamics around the 2008 global financial crisis. However, we do not observe much significant *cyclical* global co-movement in long term interest rates, apart from mostly small and high-frequency fluctuations, and beyond a decreasing trend as shown by Del Negro et al. (2019). Finally, there is significant global co-movement in GDP growth at typical business cycle frequency throughout the sample.

The global factors trace historic events well and underline the recurrent nature of global financial boom-bust episodes and associated recessions over the long period. Global dynamics during the Great Depression of the 1930s are comparable to those following the 2008 financial crisis, particularly for the financial and the credit factors.[13] However, despite stronger declines in asset prices in 2008, the bust in global GDP is less pronounced and more short-lived compared to the Great Depression. The larger and more protracted downturn in global GDP was likely associated with tighter monetary policy due to the gold standard (Almunia et al., 2010).

Accounting for an aggregate financial cycle and segment-specific cycles via the multi-level factor structure helps us uncover cycles of different lengths and amplitudes, as indicated by statistics based on the Bry-Boschan cycle dating algorithm Harding and Pagan (2002) shown in Table 1. The global credit cycle has the highest average amplitude and length (8 years), whereas the other financial cycles have shorter lengths of 3 to 5 years, and the GDP cycle 6 years. Importantly, these cyclical properties also vary over time. The longest and most ample credit and house price cycles, with an average length of 15 years and an amplitude of 9–11 standard deviations, occur in the most recent sub-sample starting in 1984. The increase is particularly strong for global house prices, which showed only small and short cycles prior to that. Spectral densities of the estimated cycles shown in the online appendix illustrate all cycle lengths relevant for the factors within the frequency domain rather than averages (Verona, 2016). They indicate that the aggregate financial cycle spans a rather wide

[13] A comparison of the factors around the episodes of the 1929 stock market crash and the 2008 financial crisis is shown in the online appendix.

Table 1
Average cycle length and amplitude, Bry-Boschan algorithm.

	1880–2013	1880–1913	1880–1913, 1923–1938	1948–1972	1973–2013	1984–2013
Average cycle length (years)						
Financial	**4**	4	4	8	5	5
Credit	**8**	9	8	8	10	15
House prices	**5**	4	4	4	10	15
Equity prices	**4**	4	4	4	5	5
Interest rates	**3**	4	3	4	4	4
GDP	**6**	7	6	6	6	8
Average Amplitude (mean peak to mean trough of cumulated factors)						
Financial	**2**	2	2	2	3	2
Credit	**4**	2	4	3	6	10
House prices	**2**	1	1	1	7	9
Equity prices	**1**	1	1	2	2	2
Interest rates	**1**	1	1	1	1	1
GDP	**3**	1	4	2	3	3

Notes: Peak and troughs identified based on cumulated estimated factors (i.e. global cycles in log levels). Peak in y_t at time t when $y_t > y_{t-1}$ and $y_t > y_{t+1}$. Average cycle length refers to average time from peak to peak.

range of the frequency spectrum, i.e. both short-lived and longer-lasting cycles, whereas the segment-specific cycles cover only specific parts of the frequency range.

Finally, factor loadings shown in Fig. 2 provide intuition on how individual time series relate to the estimated global shocks.[14] The loadings on the aggregate global financial cycle (left column) are positive for most countries for credit, house prices and equity returns, these therefore tend to jointly move together across segments and countries. The loadings are particularly large for equity prices and they increase over time in most countries. By contrast, interest rates tend to be low in most countries when credit and asset prices are high, as indicated by negative loadings. In addition, most series load positively on their respective segment-specific factor (right column), suggesting that there is co-movement across countries within each segment beyond the aggregate financial co-movement. For the global house price and equity price cycles, the size of loadings across countries is somewhat mixed. More than half of equity returns series load significantly positively on the equity price factor, including the US and UK, whereas various other countries' financial conditions seem to be fully captured by the aggregate financial cycle. This could reflect a leading role of US and UK financial cycles for the aggregate financial cycle.[15] For house price factor, there is variation over time masked by the averages: most loadings turn positive around the 1970s reflecting a synchronization in global housing prices.

4.2. Importance of global co-movement

How relevant are these common shocks for explaining fluctuations in the individual time series relative to idiosyncratic dynamics? Fig. 3 shows the shares of variance in each series explained jointly by the global factors, averaged in total and by countries or country groups. On average over the long sample period (left white bars), global co-movement explains substantial, albeit not predominant shares of fluctuations in financial aggregates. The average share of fluctuations explained by global co-movement is largest for equity prices (34 percent) and smallest for house prices (12 percent); about 20 percent of fluctuations in credit, long-term interest rates and GDP, respectively, are explained by global factors.[16]

When looking at the evolution over time based on sub-samples (black bars), global dynamics became strikingly more important for equity prices. In the most recent period, more than 50 percent of equity price fluctuations are explained by global factors across countries. This increase occurred in *all* countries and country groups in our sample. In a few countries, such as the UK, up to 60 percent of equity price fluctuations are due to global factors in the most recent sub-sample. For credit and house prices, the increase in the role of global dynamics appears much less pronounced on average, but with substantial heterogeneity across countries. In the US, UK, and the Nordic countries global dynamics have become clearly more important over time, with up to 40 percent of credit and house price fluctuations explained by global factors in the latest sub-sample. Whereas in Continental Europe and in the remaining economies, particularly Japan, the role of global factors for credit and house prices has remained stable at lower levels, or has even declined. For long-term interest rates, the role of global fluctuations decreases to 14 percent, in line with the decline in their global trend observed by Del Negro et al., 2019.

[14] Time-varying factor loadings are averaged over time for readability. The size of loadings varies over time, but mostly does not switch sign, leaving the interpretation of factors stable over time.

[15] Granger causality tests (results are available upon request) suggest that the equity price cycle Granger causes the financial cycle, but not vice versa.

[16] For ease of exposition, we focus on the joint role of the aggregate financial factor and the segment-specific factor. The online appendix includes more detailed results for all countries and splitting out the role of the two types of factors, indicating that the aggregate financial factor explains variation in all four financial variables across countries. Although it is relatively most important for equity prices, where two thirds of the variation driven by global dynamics is due to the aggregate financial factor.

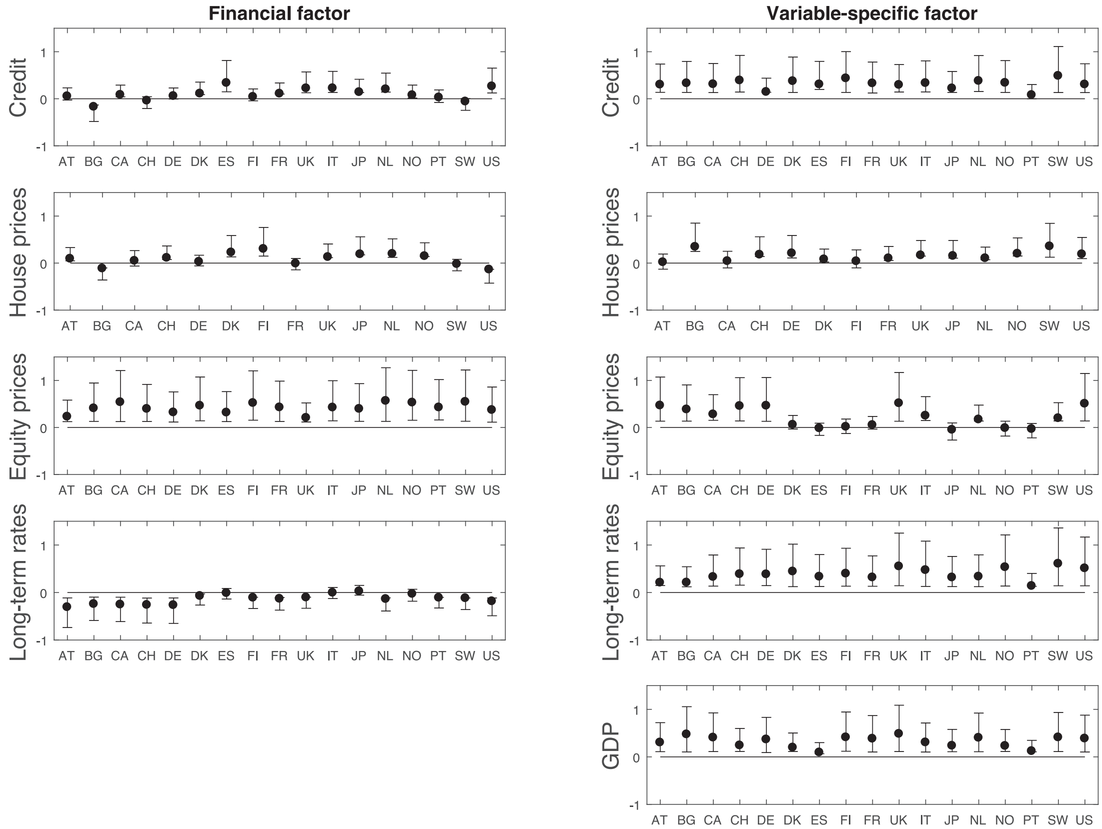

Fig. 2. Loadings by variables and countries, average over total sample period. Notes: Medians over 500 retained Gibbs draws (circle markers) and 68 percent credible sets (whiskers). Loadings are averaged over time.

Finally, we see a strong increase in the role of global co-movement for GDP growth since the early era of globalization, reflecting increases in most but not all countries.

To detect these changes over time, allowing for changes in the size and role of global shocks via time-varying parameters is essential. The posterior estimates for the time-varying loadings and stochastic volatilities (shown in the online appendix) indicate that the increased role of global dynamics for equity prices reflects, on the one hand, an increase in the volatility of global equity price shocks and, on the other hand, an increase of equity price loadings on the global aggregate and equity price factors. For credit and house prices, differences in the time-varying factor loadings drive the cross-country heterogeneity that we observe in the explained variance shares.

Overall, we find equity prices to be strongly and increasingly driven by global co-movement in all 17 economies in our sample. Small institutional differences across countries, a high degree of liquidity and fast-moving information on stock markets, and a high share of internationally trading firms participating in equity markets might make equity return dynamics a truly global phenomenon. At the same time, the observed cross-country differences in the susceptibility to global forces for credit and house prices might relate to domestic institutional characteristics and the interconnectedness of the domestic banking sector, which we next investigate more formally via panel regressions.

4.3. Role of country characteristics

We analyse the association between the susceptibility of credit and house prices to global factors and country characteristics within a panel regression setting, similarly to Arregui et al. (2018),Chudik et al. (2018), and Monnet and Puy (2019). Does the cross-country heterogeneity in explained variance shares correlate with measures of financial openness and integration, financial development, or the exchange rate regime?

We estimate k panel regressions of the form

$$log(varexpl)_{k,i,t} = \beta X^{FinInt}_{i,t-1} + \gamma X^{FinDev}_{i,t-1} + \zeta Z_{i,t-1} + \alpha_i + trend + trend^2 + u_{i,t}, \tag{7}$$

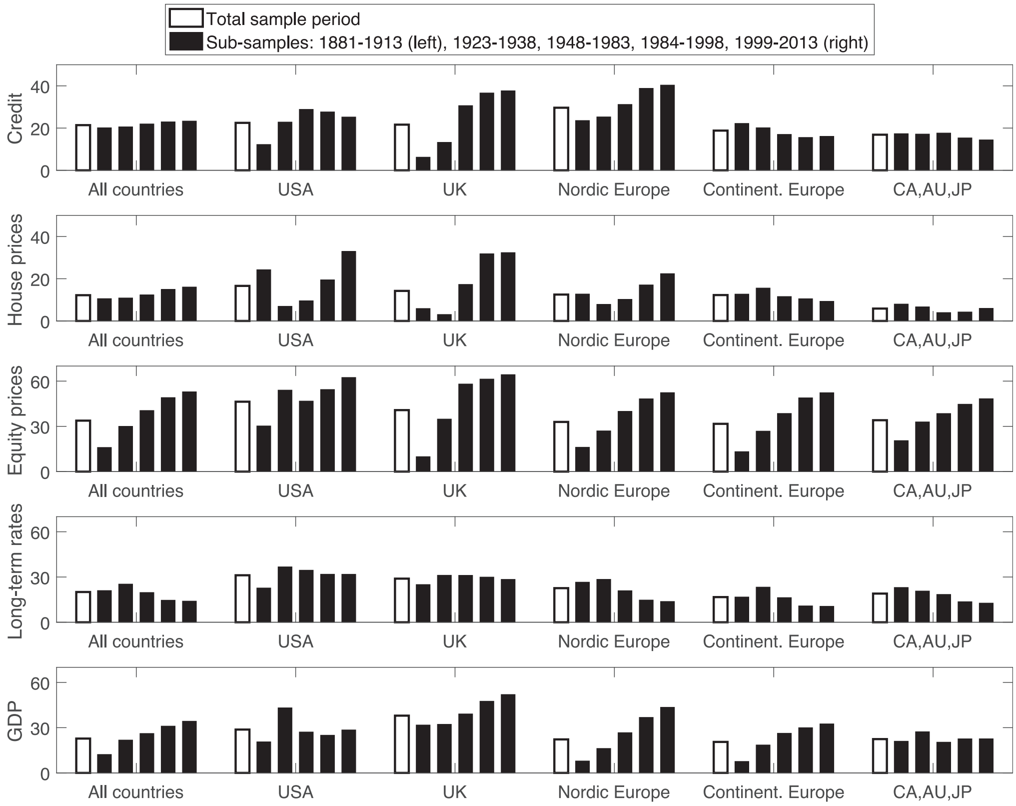

Fig. 3. Total variance explained by global factors, by countries and country groups. Notes: Share of fluctuations explained by global factors (financial factor and respective variable-specific factor), in percent. Medians over 500 retained Gibbs draws. Averages over total sample (white bars) and sub-samples 1881–1913, 1923–1938, 1948–1983, 1984 to 2013 (black bars, left to right). All countries: 17 countries (14 for house prices). Nordic Europe: Denmark, Finland, Norway, Sweden. Continental Europe: Belgium, France, Germany, Switzerland Italy, Portugal and Spain. Others: Australia, Canada, Japan.

where $log(varexpl)_{k,i,t}$ is the log of the share of variance of time series k explained by the global factors in period t and country i, where $k \in$ {credit, house prices}. The set of explanatory variables is the same in each case. Apart from country fixed effects α_i and a linear and a quadratic trend, we include the lagged values of the following three sets of explanatory variables.[17]

- $X_{i,t}^{FinInt}$ are measures of financial openness and financial integration: a dummy variable for capital controls (Ilzetzki et al., 2019), the Chinn-Ito index of capital account openness (Chinn and Ito, 2006), and a measure of cross-border lending by banks, i.e. the share of outstanding loans from nonresident banks to GDP.
- $X_{i,t}^{FinDev}$ are measures of financial development. First, the shares of private credit to GDP and private mortgage lending to GDP; these capture financial intermediation via domestic credit and those specifically related to mortgage markets. Second, the stock market turnover ratio, i.e. the value of traded stock market shares relatively to the value of listed shares, a measure of liquidity of stock markets and financial efficiency (Beck et al., 2010). Third, an aggregate measure of financial development constructed by the IMF, which is a broad indicator of the degree of the depth, access, and efficiency of both financial institutions and financial markets (Svirydzenka, 2016).
- $Z_{i,t}$ are other controls which are related to trade and economic development: a measure of trade openness, a fixed exchange rate regime dummy, and real GDP per capita.

We run the estimations over an unbalanced panel over the period 1980 to 2013 and 17 countries.[18] All explanatory variables enter in logs, except for the capital control dummy, the capital account openness index, and the fixed exchange

[17] We use lags to limit potential endogeneity issues, although results remain quite similar when including the contemporaneous values instead. As simply taking lags might not be sufficient to fully account for endogeneity issues, we do not interpret our results in terms of causality, but rather in terms of statistical associations that can provide a more structured description of our variance decomposition results.

[18] Data come from the Macrohistory and the World Bank Global Financial Development databases, details are provided in the online appendix. For house prices only 14 countries are covered.

Table 2
Panel estimation results.

Variance expl. by global factors in	Credit	House prices
	Financial openness and integration	
Capital controls	−0.48	3.75
	[0.74]	[3.51]
Capital account openness	0.04	−0.03
	[0.01]**	[0.04]
Cross-border lending	0.00	−0.00
	[0.00]	[0.01]
	Financial development	
Credit to GDP	−0.04	0.04
	[0.17]**	[0.04]
Mortgage lending to GDP	0.04	−0.02
	[0.01]**	[0.05]
Stock market turnover	0.01	0.01
	[0.00]**	[0.00]**
Financial development index IMF	0.03	0.00
	[0.00]***	[0.02]
	Trade and economic development	
Trade openness	−0.01	0.03
	[0.02]	[0.03]
Exchange rate peg	0.01	0.01
	[0.00]*	[0.01]
GDP p.c.	0.03	−0.01
	[0.05]	[0.10]
Time trend	−0.001	0.03
	[0.00]*	[0.00]
Time trend, quadratic	0.00	−0.00
	[0.00]*	[0.00]
No. of observations	482	400
No. of countries	17	14
R^2 adj.	0.53	0.18

Notes: All series are in logs, except for the dummies for capital controls and the exchange rate peg, and the indicator variable for capital account openness. All explanatory variables are lagged by one period. Estimation includes fixed effects. Robust standard errors, adjusted for 17 clusters, in brackets. ***/**/*: 1%-; 5%-; 10%- significance levels.

rate dummy.[19] Standard errors are robust to heteroskedasticity and clustered on the country level, which accounts for interdependency in standard errors across countries, also due to serial autocorrelation.

The results in Table 2 show that country characteristics can explain some of the country heterogeneity in the sensitivity of domestic credit to global cycles: various explanatory variables are significant and the R^2 reaches above 50 percent. For house prices, only 18 percent of variation is explained, possibly related to the smaller amount of observations. With regard to financial openness, the results show that a higher degree of capital account openness tends to be associated with a higher susceptibility of credit to global cycles, whereas capital controls and the interconnectedness of the banking sector are not significant. The role of financial development depends on the type of measure and the financial sub-sector to which it refers. A larger domestic credit market per se is associated with a lower susceptibility of credit to global dynamics. However, financial market development related to mortgage lending and stock market turnover, as well as development measured by the broad index do significantly enhance the impact of global dynamics. Equity markets with a high stock market turnover ratio go hand in hand with a stronger impact of global forces on both credit and house prices—this is the only significant measure in the house price regression. Here, the link between different asset prices and credit, as measured by the aggregate financial cycle, becomes evident.

Finally, the exchange rate regime plays a role as well. Pegging the exchange rate against an anchor is associated with a stronger susceptibility of credit to global dynamics. While we do not investigate monetary policy explicitly and thus can only interpret this with caution, this result might reflect the trilemma in international macroeconomics, stating that under capital account openness countries with flexible exchange rates have more scope for domestic policies which provide insulation from global dynamics (Obstfeld et al., 2005; Rey, 2015; Bekaert and Mehl, 2019). The effect is of small size and only marginally significant, indicating that exchange rate flexibility might not be the main determinant of a country's susceptibility to global dynamics, and various financial transmission channels might be at work (Obstfeld, 2015). On the other hand, the

[19] The coefficients thus represent percentage changes. The log–log specification linearises exponential growth patterns and reduces the impact of outliers and strong variations. This accounts for the fact that the dependent variables evolve smoothly, whereas the explanatory variables are much more volatile. It assumes that e.g. an increase in financial integration or financial development affects global co-movement relatively more when starting out at low levels. Similar specifications have been used in Svaleryd and Vlachos (2002) and Giovanni and Levchenko (2009).

degree of trade openness and economic development play no significant role for global financial co-movement according to our results.[20]

5. Conclusion

This paper has analysed cyclical co-movement in credit, house prices, equity prices and long-term interest rates across 17 advanced economies based on a time-varying parameter dynamic factor model and more than 130 years of data. Our analysis suggests that it is important to jointly model an aggregate global financial cycle as well as segment-specific cycles: both types of cycles explain global fluctuations and cover different cycle lengths. Our results have shown that importance, but also the cyclical characteristics of global financial cycles have changed substantially over time. Equity prices have increasingly become driven by global factors in all economies in our sample. Moreover, the large amplitude and length of global credit and house price cycles is a relatively new phenomenon and inherent to recent sample periods. The importance of the global credit and house price cycle varies across countries: panel regressions indicate that the susceptibility of credit and house prices to global dynamics is linked to financial openness and financial development.

Our results bear important policy implications. Policy makers should monitor both composite indices and individual financial segments in order to detect potential financial instabilities or GDP-at-risk. At the same time, the complex behaviour of global financial cycles, occurring at different frequencies, with varying impacts across countries, and cyclical patterns changing over time, might make it difficult for policy makers to steer cycles directly by (unilateral) policy interventions. Coordinated measures that are independent of the cycle are thus important, such as improvements in the overall transparency and international supervision of global financial linkages, or the establishment of safety nets to enhance financial stability. Country characteristics can serve as an important criterion to evaluate the need for financial stabilization and for policy coordination across countries and segments.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jimonfin.2023.102801.

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[20] Arregui et al. (2018) consider advanced and emerging economies but a shorter sample period in a comparable analysis. They also find the sensitivity of domestic financial conditions to global financial shocks to increase with financial integration and openness and to decline with financial development. They do find a positive role for trade openness, but argue that this might reflect omitted indirect financial linkages.

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