BANK OF ENGLAND

Staff Working Paper No. 867

Global financial cycles since 1880

Galina Potjagailo and Maik H Wolters

May 2020

BANK OF ENGLAND

Staff Working Paper No. 867

Global financial cycles since 1880

Galina Potjagailo[(1)] and Maik H Wolters[(2)]

Abstract

With the aim to provide a detailed understanding of global financial cycles and their relevance over time, we analyse co-movement in credit, house prices, equity prices, and interest rates across 17 advanced economies over 130 years. Using a time-varying dynamic factor model, we observe global co-movement across financial variables as well as variable-specific global cycles of different lengths and amplitudes. Global 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 much more pronounced and protracted since the 1980s, but their relevance increased for a sub-group of financially open and developed economies only. Panel regressions indicate 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 the cross-country heterogeneity in financial market characteristics therefore matters for the design of appropriate financial stabilization policies across countries and sectors.

Key words: Financial cycles, financial crisis, global co-movement, dynamic factor models, time-varying parameters, macro-finance.

JEL classification: C32, C38, E44, F44, F65, G15, N10, N20.

(1) Bank of England. Email: galina.potjagailo@bankofengland.co.uk
(2) University of Wuerzburg, Kiel Institute, and IMFS at Goethe University Frankfurt. Email: maik.wolters@uni-wuerzburg.de

The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or its committees. We are grateful to we are very grateful to Thorsten Beck, Fabio Canova, Ambrogio Cesa-Bianchi, Philipp Hartmann, Evi Pappa, Carmen Reinhart for highly valuable comments and suggestions. We also thank the participants of the 8th IWH-INFER-AEEP-Workshop, the Bundesbank Conference on Financial Cycles and Regulation, the International Association for Applied Econometrics 6th Annual Conference, the 1st Workshop for Women in Macroeconomics, Finance and Economic History, the 2019 Annual Meeting of the Central Bank Research Association, the 34th Annual Congress of the European Economic Association, the 2019 Annual Meeting of the Society for Economic Measurement, the 2019 Annual Meeting of the German Economic Association, the 2019 Bamberg Behavioral Macroeconomics Workshop, as well as internal seminars at the Bank of England, European Central Bank, the Kiel Institute, and the Kiel University for valuable feedback.

The Bank's working paper series can be found at www.bankofengland.co.uk/working-paper/staff-working-papers

Bank of England, Threadneedle Street, London, EC2R 8AH
Email enquiries@bankofengland.co.uk

ISSN 1749-9135 (on-line)

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). While this has brought many advantages in terms of risk diversification and an efficient flow of funds, the 2008 global financial crisis illustrated major risks. Credit and various financial asset classes can exhibit joint boom-bust episodes with potentially severe repercussions to the real economy (Iacoviello, 2015; Jordà et al., 2015a,b; Menden and Prõano, 2017; Bluwstein et al., 2020). At the same time, fluctuations in financial quantities and prices display a strong degree of commonality across advanced countries, such that financial fluctuations can quickly take a global dimension (Eickmeier and Hofmann, 2013). Policy makers thus face trade-offs between domestic policy objectives and cross-country spillovers (Obstfeld, 2015). At the extreme, domestic financial conditions might be driven by a "global financial cycle" and by monetary policy in centre economies, outweighing the role of domestic fundamentals (Rey, 2015; Bruno and Shin, 2015; Cesa-Bianchi et al., 2018).

In view of this, the empirical literature on global financial co-movement is rapidly growing. Yet, the picture of the global financial cycle is still mixed. Helbling et al. (2011), Hirata et al. (2012), Miranda-Agrippino and Rey (2015) and European Central Bank (2018) find a strong and recently increasing role of global co-movement for financial variables. Recent papers, however, question the quantitative importance of the global financial cycle (Cerutti et al., 2019), its increased role over time (International Monetary Fund, 2017), or find evidence only for asset-specific global cycles rather than a joint global financial cycle (Ha et al., 2017). The mixed findings might relate to two facts. Existing studies focus on rather short samples of 25 to 40 years, despite financial cycles having a low frequency (Claessens et al., 2012; Borio, 2014; Rünstler and Vlekke, 2018), and there is no consensus yet regarding which financial aggregates are relevant measures of global financial cycles. Some of the existing studies look at risky equity returns only, some at credit and various asset prices individually, others consider composite indices of financial conditions, and yet others look at capital flows.

Against this background, we contribute to a detailed understanding of global financial cycles and their relevance. We analyse global cycles in credit, house prices, equity prices and long-term interest rates across 17 advanced economies based on a Bayesian dynamic factor model with time-varying loadings and stochastic volatilities. We use over 130 years of data from the Macrohistory Database of Jordà et al. (2017) and Knoll et al. (2017), and our sample covers more than 50% of world GDP over the sample period.

Our main innovation to the literature is two-fold. First, we provide evidence for global financial co-movement at different levels—across various asset price and credit measures (financial factor) as well as specific to each measure (variable-specific factors)—while controlling for macro-financial linkages (macro-financial factor). Second, we consider a long time span in a time-varying parameter model which allows to analyse the properties of recurrent cycles over time and to compare two large-scale global incidents of financial turmoil, the Great Depression and the Great Recession. We show that, although financial co-movement is not an entirely new phenomenon from a historical perspective, global co-movement has become more relevant for financial fluctuations over time, and global credit and house price cycles have become more ample and protracted. Our analysis provides a comprehensive picture of global financial cycles and bridges the gap between existing studies that focus either on the cyclical properties of credit (see, e.g., Borio, 2014) or on global co-movement mostly in risky asset prices (Miranda-Agrippino and Rey, 2015).

We investigate two main research questions. First, what are the main characteristics of global financial cycles: what types of cycles are there and what are their cyclical properties? Second, how relevant is global financial co-movement from a historical perspective in terms of explaining fluctuations in the data?

Regarding the first research question, we find evidence for global co-movement at different levels of aggregation, and that the factors trace historic events well. There is a global financial factor capturing joint co-movement between credit, asset prices and long-term interest rates. This factor displays both high and medium frequency fluctuations and compares very closely to the global financial factor estimated by Miranda-Agrippino and Rey (2015) for the period from 1990 to to 2012. The latter is based on almost 900 time series, while our financial factor is estimated on 65 time series only, due to the long sample. Beyond that, there is a global credit cycle and a global house price cycle which both became more prolonged and ample since the 1980s reaching a length of about 15 years, as well as a global equity price cycle of a length of 3 to 5 years. Finally, there is a global GDP factor showing cycles of 2 to 8 years, and increasingly also some more protracted fluctuations. We also find evidence for a global macro-financial factor, but the size and relevance of macro-financial shocks declined over time.

Regarding the second question, we find that on average global co-movement explains large, but not dominant shares of fluctuations in financial aggregates. For equity prices, the picture is special: the role of global factors increased steadily and strongly over the historical time span in all economies we consider; today, more than half of equity price fluctuations are due to global dynamics. This result reflects larger global equity price shocks as well as an increased dependence of most equity prices series on global shocks. For the other financial aggregates, the role of global co-movement is on average smaller and not a new phenomenon from a historical perspective. However, for credit and house prices, there are differences across countries: the susceptibility to global dynamics increased in the UK, the US and in Nordic European countries, but remained constant or even declined slightly in most other considered countries. Finally, the global GDP factor today explains an unprecedented share of 40 percent of GDP fluctuations on average across countries.

Our findings imply that both composite indices and individual financial sectors should be carefully monitored by policy makers. In this, both slow-moving variables such as credit as well as fast-moving variables such as equity prices can be jointly relevant for financial stability. We show that global financial cycles that represent co-movement in equity prices and those that represent joint co-movement across credit and asset prices operate at frequencies that are roughly similar to those of business cycles. Global credit and house price cycles operate at lower frequencies. Thus, a mix of different policy instruments including macroprudential measures aiming at the stabilization of low frequency credit and housing cycles and monetary policy measures aiming at the stabilization of financial variables that move in parallel with the business cycle might be needed (Gambacorta and Murcia, 2017; Borio et al., 2019). The role of global dynamics is most pronounced in equity markets, but for a subgroup of financially open countries the role of global dynamics for credit and house prices has been high for the last 40 years, too. When such dynamics in asset prices and credit occur simultaneously and on a global scale—as captured by the financial factor—leverage and therefore risks to financial stability might increase substantially (Jordà et al., 2015b). With potentially little room for maneuver for domestic monetary authorities, newly designed policy responses might be required to "tame" the global financial cycle via internationally coordinated macroprudential policy, financial regulation and monetary policy (Rajan, 2015; Cecchetti and Tucker, 2016; Gopinath, 2017).

Our analysis and findings relate to various existing studies that also look at global financial co-movement or cyclical properties of financial aggregates, although they focus on recent sample periods and either on slow-moving variables such as credit or house prices only, or instead on financial market data such as equity prices. Our findings confirm the results from earlier papers that observe a financial cycle length of 15 to 20 years over recent sample periods, where the (domestic) financial cycle is defined in terms of credit and house prices (see, e.g., Claessens et al., 2012; Borio, 2014; Rünstler and Vlekke, 2018; Lang and Welz, 2018). Our finding of time-variation in the cyclical properties of global credit and house prices is in line with Filardo et al. (2018), who, based on a long sample period, find that the domestic US credit cycle became more protracted during the post-War period. Finally, our result of little evidence for common global macro-financial shocks, at least in recent decades, is in line with the findings of Cesa-Bianchi et al. (2018) based on a factor-augmented PVAR model and Ha et al. (2017) based on a dynamic factor model.

The historical perspective also relates our analysis to recent studies which use similar long data sets to analyse global co-movement of financial variables, but differ with respect to the variables covered and methodology. Jordà et al. (2019) analyse global asset-specific co-movement and Meller and Metiu (2017) study global co-movement of credit, based on biletaral cross-country correlations, respectively, wheres Bekaert and Mehl (2019) analyse global co-movement of equity returns within a factor model. We confirm the finding from these studies of a growing role of global dynamics for equity prices over a long period. Regarding other financial variables our findings go further. We observe protracted and ample global cycles in credit and house prices over recent decades, and that the relevance of these cycles increased for a subset of economies only.

Investigating this result further based on panel regressions, we find that a country's financial susceptibility to global forces increases systematically with the degree of financial openness and financial integration. Also, while we do find that a large and developed domestic financial sector is in principle less dependent on global dynamics, this result is reversed when credit is linked with developed mortgage markets. Understanding cross-country heterogeneity related to differences in institutional characteristics and the interconnectedness of the financial system is therefore important when thinking about the coordination of financial stabilization policies across countries and sectors.

The remainder of the paper is organised as follows. Section 2 presents the historical data set and shows stylised facts on historical global financial co-movement. Section 3 describes the time-varying dynamic factor model with a multi-level factor structure and section 4 presents the results and discusses some robustness checks. Section 5 concludes.

2 Data and Descriptive Statistics

We use annual data on GDP, credit, house prices, equity prices, and long-term interest rates for 17 advanced economies from 1880 to 2013. The data are taken from the Jordà-Schularick-Taylor Macrohistory Database.[1] Nominal variables are deflated with CPI. We include data for 17 countries for each of these variables, except for house prices, for which we include data for 14 countries only, because of limited data availability.[2] Overall, 82 time series are included in the model. We take logs of all time series except of interest rates, and we take first differences of all series. Since the differenced series show long-run trends, we compute deviations from centred moving averages of $\pm$ 8 years.[3]

2.1 World Wars, Missing Values, Stochastic Volatility

The historical data pose various challenges for the empirical analysis that we need to take into account prior to estimation as well as when interpreting the results.

First, our sample period includes the two World Wars from 1914 to 1918 and from 1939 to 1945. During these years and the first years after the wars, data points are missing and available data show strong fluctuations. These reflect the extreme economic environment

[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]Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, UK, US. House price data for Spain, Italy and Portugal are only available from the 1970s or later, and are not included in the baseline analysis. In a specification including these series, results remain very similar, but estimation is less stable due to a high number of missing values.

[3]The approach closely corresponds to the one applied in Stock and Watson (2012). Endpoints are handled by truncating the moving average and renormalizing the weights to sum to one. Figures A1 to A5 in the appendix show the transformed series for all countries.

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. Although the dynamic factor model allows for gradual variation of shock variances, strong outliers can distort the results for the periods which we are actually interested in—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 (overall 18 years) 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.

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 historical sample. Table 1 shows summary statistics regarding the total number of observations and the number of missing values for each of the financial variables. After excluding the World War periods, the number of missing values is relatively small, representing 1 percent (long-term interest rates) to 10 percent (house prices and equity prices) of total observations. However, 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. Hence, the large share of missing data during the early period implies that we can learn less from the data during this period, and that our global factors refer to only a subset of countries for the early sub-period. Also, the comparability of the data across countries is likely to be weaker in the early period.[4]

Third, descriptive statistics presented in Table A2 in the appendix show that there are large changes over time in the level and the volatility of the time series. This calls for a flexible model allowing for stochastic volatility.

These challenges regarding changing time series properties and evolution in data quality underline the need for using a flexible model that accounts for missing values beyond simple interpolation 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 implicitly 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.

[4]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)).

Table 1: Data summary statistics.

	Credit	House prices	Equity prices	LT interest rates
Number of countries included	17	14	17	17
Total sample, 1880 to 2013				
No. observations (130 years)	2278	1876	2278	2278
No. observations, excl. WWs (116 years)	1972	1624	1972	1972
No. missing values	85	168	175	5
No. outliers set to missing	6	6	5	10
Share missings / total observations (excl. WWs)	4.6%	10.7%	9.1%	0.8%
Early era of globalization, 1880 to 1913				
No. observations (34 years)	578	476	578	578
No. missing values	78	143	167	1
Share missings / observations	13.5%	30.0%	28.7%	0.2%
Share missings 1880-1913 / total missings	85.7%	82.2%	92.8%	6.7%

Notes: Data from the Macrohistory Database. Numbers of missing values do not include periods 1914-1922 to 1939-1947 (World War years). There are no missing values for GDP and CPI (17 countries and 1972 observations, respectively).

3 Methodology

To address time-variation over the long period carefully and to model global co-movement at different levels of aggregation, we estimate a dynamic factor model (DFM) with time-varying factor loadings and stochastic volatility, following the methodology developed in Del Negro and Otrok (2008) and applied in Ritschl et al. (2016). We first introduce the model abstracting from the multi-level factor structure which we explain afterwards.

A panel of time series is described in terms of a small set of dynamic factors, representing unobserved components that affect all time series jointly, and in terms of dynamic idiosyncratic components, specific to each time series. The time series relate to the factors and idiosyncratic components 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 $F_t = [f_{1,t}, ..., f_{K,t}]$ for $t = 1, ..., T$ and $U_t = [u_{1,t}, ..., u_{n,t}]$ 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 $\chi_t \sim N(0_{n\times 1}, I_{n\times n})$. Hence, the factors are assumed to be orthogonal to each other and not to affect each other at lags.[5] 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).[6] 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 $\Omega_\eta = diag(\sigma^2_{\eta 1}, ..., \sigma^2_{\eta K}, \sigma^2_{\eta K+1}, ..., \sigma^2_{\eta K+n})$. The variances $\sigma^2_{\eta 1}, ..., \sigma^2_{\eta K}$ correspond to the volatilities of factors, and $\sigma^2_{\eta K+1}, ..., \sigma^2_{\eta K+n}$ 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:

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

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

Additional identification restrictions are needed 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.

[5]This is a typical assumption in the literature, see for instance Banbura et al. (2013) and Miranda-Agrippino and Rey (2015), 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.

[6]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, 2015; Ha et al., 2017).

3.1 Multi-Level Factor Structure

In the baseline specification, we include data on GDP growth and four financial series. We thus require a factor model which is able to account for potential common dynamics between real and financial aggregates, between different financial aggregates, and for individual aggregates 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 and Eickmeier (2016) and Ha et al. (2017).

We first define a global macro-financial factor. This factor represents co-movement which is present in all time series in the data set, and, most importantly, it accounts for linkages between the real side, represented by GDP growth, and the financial side. Second, we define a global financial factor which captures common shocks driving all financial variables across all countries in the data set. Finally, for each variable we include a variable-specific factor which captures co-movement across countries that is specific to the respective variable.[7]

The observation equation for the multi-level model reads as follows:

$$\begin{bmatrix} Y_t^{gdp} \\ Y_t^{fin_1} \\ \vdots \\ Y_t^{fin_r} \end{bmatrix} = \begin{bmatrix} \Lambda_t^{gdpMF} & 0 & \Lambda_t^{gdp} & 0 & \dots & 0 \\ \Lambda_t^{fin_1MF} & \Lambda_t^{fin_1F} & 0 & \Lambda_t^{fin_1} & \dots & 0 \\ \vdots & \vdots & \vdots & & \ddots & \\ \Lambda_t^{fin_rMF} & \Lambda_t^{fin_rF} & 0 & 0 & \dots & \Lambda_t^{fin_r} \end{bmatrix} \begin{bmatrix} f_t^{MF} \\ f_t^F \\ f_t^{gdp} \\ f_t^{fin_1} \\ \vdots \\ f_t^{fin_r} \end{bmatrix} + \begin{bmatrix} U_t^{gdp} \\ U_t^{fin_1} \\ \vdots \\ U_t^{fin_r} \end{bmatrix}, \quad (6)$$

where Y_t^{gdp} are the GDP growth series and $Y_t^{fin_1}, ..., Y_t^{fin_r}$ are the $r = 4$ financial series included in the model, over N countries, respectively. All time series can a priori be driven by the macro-financial factor f_t^{MF}, as its loadings remain unrestricted. By contrast, we do restrict the loadings to the other factors such that only the financial series, but not GDP, respond to the financial factor f_t^F, and such that the time series for each variable depend on their corresponding variable-specific factor, f_t^{gdp} or $f_t^{fin_1}, ..., f_t^{fin_r}$, but not on the other variable-specific factors. U_t^{gdp} and $U_t^{fin_1}, ..., U_t^{fin_r}$ 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 equations (2) to (4), the loadings evolve as random walks as specified in equation (5).

[7]Studies focusing on business cycle co-movement among large numbers of countries have observed the presence of regional dynamics, with a convergence within advanced economies and a decoupling from emerging market dynamics (Kose et al., 2003, 2012; Carstensen and Salzmann, 2017; Berger and Richter, 2017). As we focus on advanced economies only, which exhibit similar characteristics and are closely linked via financial markets, we expect regional decoupling to be limited in our case and do not include regional factors. Further, defining country groupings is not obvious over the long sample period, and additional assumptions would be needed with this respect. For instance, the closer integration among euro area countries only refers to the latest part of the sample. In the early part of the sample, integration of euro area economies might have been stronger with the UK, which had close links to Australia and Canada via the British Empire.

3.2 Priors

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

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

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

for $i = 1, ..., n.$ and for $j = 1, ..., K, K+1, ..., K+n$. The scale hyperparameters s^2 represent beliefs regarding the amount of variation in the innovations, and the degrees of freedom hyperparameters ν 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. In this way, we force the parameters to capture structural and institutional changes affecting the degree of global financial integration, as opposed to short-term global cyclical fluctuations, which are captured by the factors. At the same time, we incorporate the belief that smooth changes in the time series' susceptibility to global shocks may well have been sizable over the long sample period, due to long-run 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 variance of the former to be somewhat larger compared to the latter.[8] 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 $\nu_\epsilon = \nu_\eta = 134 = T$.

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

$$\phi_{prior} \sim N(0_{q\times 1}, \underline{V_\phi}),$$

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

$$\theta_{prior} \sim N(0_{p\times 1}, \underline{V_\theta}),$$

where $\underline{V_\theta} = \tau_2 diag(1, \frac{1}{2}, ..., \frac{1}{p})$ and $\tau_2 = 1$.

3.3 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

[8]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.

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.[9]

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 draws for different parameters and state variables and by calculating the recursive means and variances of the draws, which gave satisfactory results.[10]

4 Results

In the following, we first provide answers to the question of how global financial cycles look: we present our estimates of the global factors, their factor loadings and cyclical properties (section 4.1). Then we provide evidence on how relevant global dynamics are over time: we look at the shares of variances explained by global factors in the data (section 4.2), and we check how differences in these shares relate to country characteristics (section 4.3).

4.1 Global Financial Cycles

Figure 1 shows the medians from the posteriors of the seven factors measuring global cycles, together with 68 percent credible sets. The global factors are estimated precisely, at least for the period since 1900. Throughout the long sample, there is significant global co-movement of a cyclical nature jointly across variables, i.e. between GDP and financial variables (the

[9] We eliminate the idiosyncratic terms from the state vector, so that its dimension does not increase with n, via quasi-differencing equation (1), as in Quah and Sargent (1993) and Del Negro and Otrok (2008). In order to estimate the autoregressive coefficients in equation (3) via maximum likelihood, we need a series of error terms U_t without missing values. Therefore, we additionally sample the idiosyncratic components conditional on the factors, the loadings, the stochastic volatilities and the 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.

[10] Figure A6 shows recursive means and variances of the Gibbs sampler draws for selected state variables.

macro-financial factor) as well as between credit and various asset prices (the financial factor). The aggregate factors have a smaller amplitude compared to the variable-specific factors. The factors have different cycle lengths and the cyclical properties of some of the factors change over time. We analyse this in greater detail in section 4.1.2.

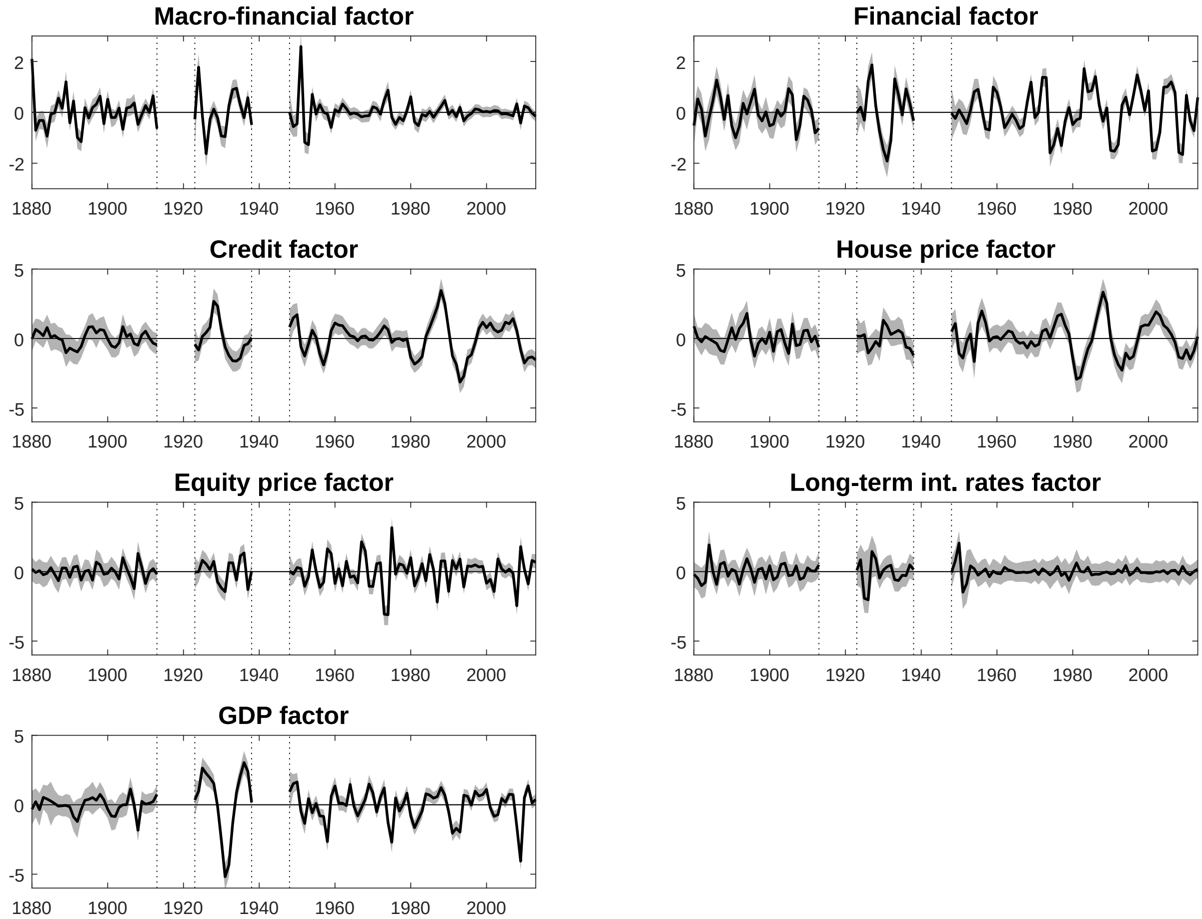

Figure 1: Global Factors
Notes: The macro-financial (financial) factor represents common dynamics across all (all financial) variables and countries. The remaining factors represent common variable-specific dynamics across countries. Solid lines show the posterior median, gray areas show the 68 percent credible sets. Data during the two World Wars and the years thereafter (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).

The global macro-financial factor predominantly captures the boom-bust episodes of the early era of financial globalization and the Great Depression. The global financial factor shows significant fluctuations over the whole sample and captures important historical events like the Great Depression or the recent Global Financial Crisis. This factor represents joint co-movement in credit and asset prices and is thus most closely related to what Rey (2015) defines as the global financial cycle. In Figure 2, we compare that factor to the global financial factor of Miranda-Agrippino and Rey (2015). The authors estimated their factor based on more than 850 monthly series of asset prices, bond prices and commodity prices using a dynamic factor model. For the comparison, we transform their factor to an annual basis and standardise it. From 1990 onward, our financial factor compares remarkably well to their factor, despite being extracted from a much smaller set of variables.

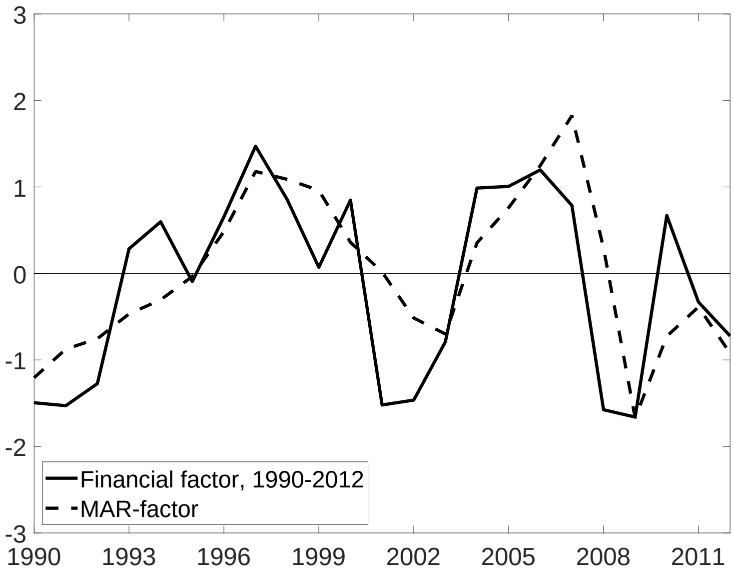

Figure 2: Financial factor compared to factor by Miranda-Agrippino and Rey (2015).
Notes: Solid lines show the posterior median of our global financial factor from 1975 onward. MAR-factor (dashed lines) is estimated by Miranda-Agrippino and Rey (2015) based on a dynamic factor model from a sample of 858 monthly price series from 1990 onwards. For the comparison, we transformed their factor to the annual frequency and standardised it.

Conditionally on the macro-financial and financial factors, there is substantial variable-specific global co-movement in credit, house prices and equity prices. Co-movement in credit is pronounced during the inter-war period. In addition, starting from the 1970s there are long and ample parallel fluctuations in global credit and global house prices.[11] The global equity price factor shows short cycles and captures all important stock market booms and busts since 1929. Only the long-term interest rate factor is insignificant and shows no fluctuations during the post-war period, with loadings also being close to zero. As we show in section 4.2, the macro-financial and the financial factor capture most of the global fluctuations in long-term interest rates. Finally, there is significant global GDP-specific co-movement since the beginning of the 20th century above and beyond the fluctuations captured by the macro-financial factor. The global GDP factor captures all major business cycles at least since the inter-war period.

4.1.1 Factor loadings

Figure 3 shows the loadings of the time series to the factors averaged over time (circle markers), together with 68 percent credible sets (whiskers). The loadings provide an idea of how individual time series relate to the estimated global shocks and thus allow to interpret the factors better. While the size of many loadings varies over time, most loadings do not switch sign over time (Figures A7 to A9 in the appendix).

[11]This finding remains robust when we include house price series for Italy, Spain and Portugal into the estimation. Results for this specification are available upon request.

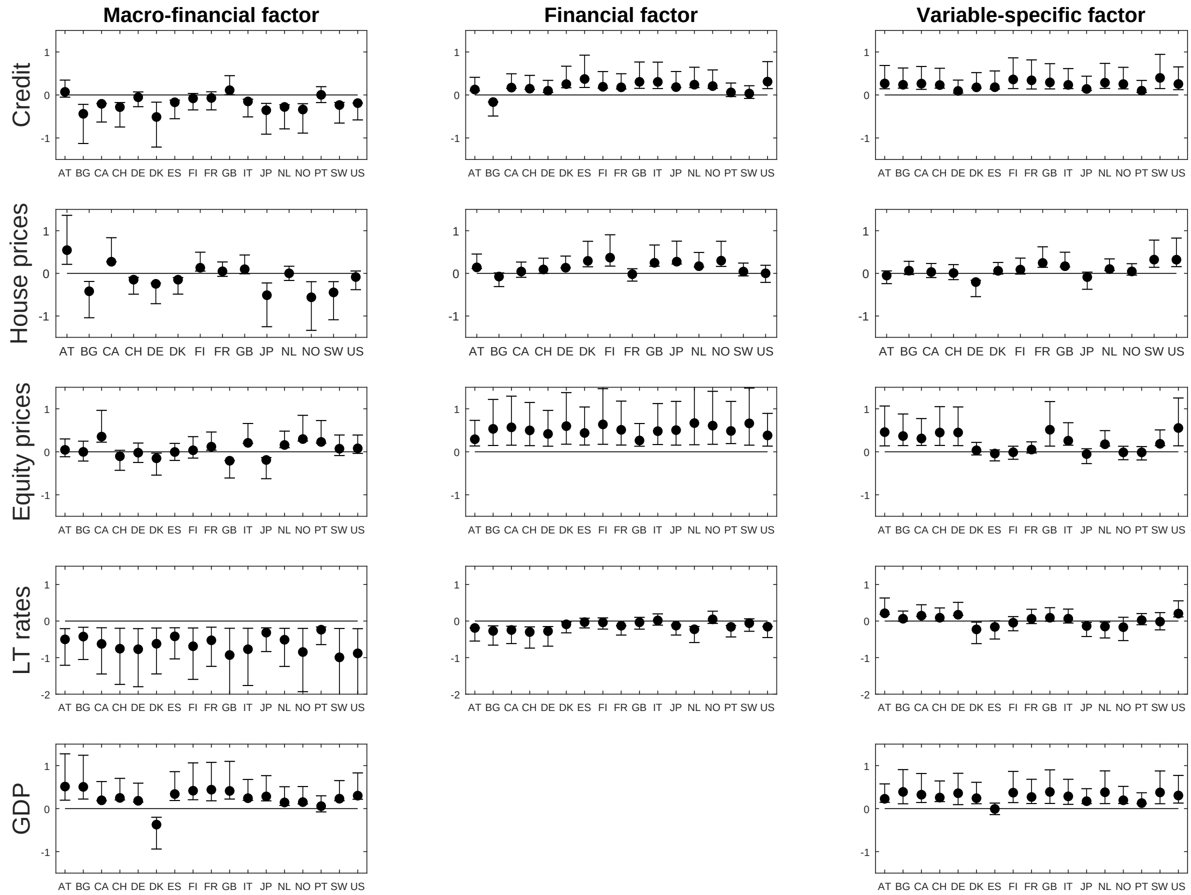

Figure 3: Loadings by variables and countries, average over total sample period.
Notes: Medians over 500 retained Gibbs draws (circle markers) and 68 percent credible sets (whiskers). Loadings are averaged over time. GDP series do not load on the financial factor via the multi-level factor structure.

The loadings to the macro-financial factor reflect that macroeconomic boom periods are often associated with low interest rates: almost all GDP series are associated positively and significantly with the macro-financial factor, whereas long-term interest rates load markedly and significantly negatively. By contrast, the loadings of the other financial aggregates are positive for some countries, but negative for others. They are only significant for about half of the economies, indicating that there are no globally synchronised contemporaneous co-movements between GDP and these series, but rather macro-financial linkages for a few countries only. Nonetheless, additional spillovers between global macroeconomic and financial factors might be present at time lags, something that we do not control for.

The financial factor captures global joint co-movement of the four financial variables. Most credit series, all equity price series, and about half of the house price series load significantly positively on that factor, whereas long-term interest rates in about half of the countries load negatively. Hence, the volume of credit and housing and equity returns tend to jointly move together, whereas interest rates tend to be low when credit and asset prices are high. The loadings to the financial factor are particularly large for equity prices and increase substantially over time in most countries (Figure A8). For credit and house prices, the loadings to the financial factor increase towards the end of the sample in about half of the countries, including the US, UK and some Nordic European countries, reflecting the boom-bust cycles in credit-financed real estate since the 1980s in these economies.

Finally, we turn to the variable-specific factors. All credit series load significantly positively on the credit factor throughout the sample period. Only some of the house price series load significantly positively on the global house price factor over the total sample period. However, most loadings to the house price factor increase and turn positive around the 1970s reflecting a synchronization in global housing prices. At the end of the sample period, the house price factor represents to a greater extent truly global co-movement, with only the German and Japanese loadings remaining negative (Figure A9).[12] More than half of equity returns series load significantly positively on the equity price factor, with the US and UK loadings being largest. For some countries, however, the loadings on the equity price factor are close to zero; the global dynamics in their equity prices seem to be fully captured by the financial factor.[13] Finally, almost all GDP series load positively on the global GDP factor, so that this can be interpreted as a global business cycle.

4.1.2 Cyclical properties of global factors

The global factors appear to exhibit different and potentially time-varying amplitudes and cycle lengths. In order to assess the cyclical properties of the factors in a more rigorous manner, we identify peaks and troughs in the factors via the Bry-Boschan cycle dating algorithm as in Harding and Pagan (2002), and we consider the factors within the frequency domain via spectral density analysis. In both analyses, we consider the total sample period as well as various sub-samples.

Table 2 shows for each factor the average cycle length according to the Bry-Boschan algorithm, i.e. the average number of periods between subsequent peaks, as well as the maximum (average) amplitude in terms of the distance between the maximum (average) peak and lowest (average) trough.[14] Over the total sample period, the credit factor shows the highest cycle length with 10 years. The house price factor and the GDP factor show a standard business cycle length of 7 years, respectively. The other factors all have a shorter length of 4 to 5 years. Also the amplitudes of GDP, the credit and house price factors are higher compared to the other variables.

There is, however, substantial variation over time in cycle length and amplitude for

[12]The result for Germany is in line with the result of European Central Bank (2018) that cycles in credit and house prices in Germany differ from those in other European countries.

[13]We also run Granger causality tests for the different factors (results are available upon request), and find that the equity price factor Granger causes the financial factor, but not vice versa. Hence, the fact that we observe large positive loadings of US and UK equity prices on the equity price factor, while for other economies, equity price dynamics are rather captured by the financial factor, might reflect that the US and UK stock markets lead the dynamics of other stock markets.

[14]To apply the Bry-Boschan algorithm, we need the series to be in log-levels and we thus cumulate the estimated factors over time. The algorithm identifies a peak in y_t at time t when $y_t > y_{t-1}$ and $y_t > y_{t+1}$. Results remain qualitatively similar when peaks are identified relative to two lags and leads.

Table 2: Cycle length and amplitude, Bry-Boschan algorithm.

	Total sample: 1880-2013	Early era: 1880-1913	Early era+ inter-war: 1880-1913, 1923-38	post-war /Bretton-Woods: 1948-1972	post-Bretton-Woods: 1973-2013	Great Moderation/FC: 1984-2013
Average cycle length (years)						
Macro-financial factor	**4**	4	4	5	5	4
Financial factor	**5**	4	4	6	5	5
Credit factor	**10**	9	10	8	10	15
House price factor	**7**	4	5	6	14	15
Equity price factor	**4**	3	4	4	4	4
LT interest rate factor	**4**	4	5	4	5	4
GDP factor	**7**	11	13	4	7	10
Average Amplitude (mean peak to mean trough of cumulated factors)						
Macro-financial factor	**1**	1	1	1	0	0
Financial factor	**2**	1	1	2	3	3
Credit factor	**4**	2	4	3	7	11
House price factor	**3**	1	1	2	10	10
Equity price factor	**1**	1	1	2	2	1
LT interest rate factor	**1**	1	1	1	0	0
GDP factor	**3**	2	5	1	4	5
Maximum Amplitude (max. peak to min. trough of cumulated factors)						
Macro-financial factor	**4**	2	4	3	2	1
Financial factor	**6**	3	5	3	6	5
Credit factor	**12**	4	8	6	12	12
House price factor	**11**	4	4	5	11	10
Equity price factor	**7**	2	3	4	6	4
LT interest rate factor	**4**	2	4	2	1	1
GDP factor	**14**	3	14	5	7	7

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. Sub-sample "early era+inter-war" excludes WWI.

some of the factors. In the early part of our sample, the financial and variable-specific cycles show less regular cycles and somewhat smaller amplitudes compared to the global business cycle. Cycles were particularly short and of low amplitude in the Bretton-Woods period, but strikingly, the cycle length and amplitude of the credit and house price factors increased substantially thereafter. The longest and most ample credit and house price cycles of 15 years length occurring in the most recent sub-sample starting in 1984. The GDP factor exhibits a long and ample cycle of about 14 years during the Great Depression, followed by short-lived cycles after World War II. Since the 1970s, the global business cycle length and amplitude has increased substantially, although to a lesser extent than in the case of global credit and house prices. By contrast, there is little change over time in the cyclical properties of the equity price and long-term interest cycles.

In addition, Figure A10 in the appendix shows the spectral densities of the estimated factors. They represent all cycle lengths relevant for the factors within the frequency domain instead of considering average lengths (see Verona (2016) and Strohsal et al. (2019) for related analyses for domestic financial cycles). The results confirm the observations from the Bry-Boschan algorithm-based analysis: macro-financial and financial factors span a rather wide range of the frequency spectrum, whereas the variable-specific factors cover only specific parts of the frequency range. The credit and house price factors show increasingly prolonged cycles over time, whereas global equity price fluctuations occur at a high frequency.

4.1.3 What we learn from looking at historical global financial cycles

Taken together, we observe common cycles specific to individual financial sectors as well as a aggregate financial cycle throughout the historical sample. The global credit and house price cycles, and to a lesser extent also the global financial cycle, became more prolonged and ample since the 1970s, while the equity price cycle kept its mostly high frequency fluctuations. Controlling for both aggregate and variable-specific global cycles turns out an important ingredient of our model, as it allows to capture substantial global financial fluctuations at different economically relevant frequencies. In the following, we discuss the findings we have so far in terms of how our global factors relate to historical events, and in terms of how our findings add to the understanding of global financial cycles from the existing literature.

Global factors and historical events. Our global factors trace historic events well. Dynamics during the "early era of financial globalization" between 1880 and 1913 are mostly reflected by fluctuations in the two aggregate factors (Figure 1). The macro-financial factor shows boom-bust episodes of different length during the Depression 1882-85 as well as the Panics of 1893, 1901, and 1907, respectively. The financial factor shows a boom starting in the mid-1880s after the Depression of the early 1880s, followed by a bust in 1893, and boom-busts around the 1907 and 1910/11 panics. The variable-specific global factors are mostly insignificant during the early era, except for marginally significant declines around 1893, and short-lived fluctuations of the equity price factor around 1907 and 1911.

The Great Depression appears overall not too different from the Great Recession, according to our results. This is illustrated in Figure 4 which compares the estimated factors at two periods of time, with $t = 0$ set to the year 1930 (dashed lines) versus $t = 0$ set to 2008 (solid lines). The fluctuations in global credit are very similar across the two episodes. Also the global financial factor behaves quite similarly: its slump is quite prolonged in both cases, being continuous during the Great Depression, but rather a double-dip decline during the Great Recession and the euro area sovereign debt crisis. Greater differences occur for global asset prices. The slump in global equity prices is less severe, but more prolonged during the Great Depression. Housing prices did not contract during the Great Depression on a global scale, but there is a global housing slump around the Great Recession reflecting that the global financial crisis originated in the real estate sector. Global GDP initially behaves very similarly during the two episodes. However, despite the stronger declines in asset prices, the busts in the global macro-financial cycle and in global GDP are less pronounced and more short-lived in the Great Recession compared to the Great Depression. Thus, on the one hand, our results underline the recurrent nature of global financial boom-bust episodes and associated recessions over the historical time period. On the other hand, the larger and more protracted downturn in global GDP during the Great Depression was likely associated with tighter monetary policy in place due to the gold standard. During the recent episode, the aggressive use of monetary and fiscal policy measures, together with the prevailing flexible exchange rate frameworks, alleviated the drop in global GDP (see, e.g., Almunia et al., 2010).

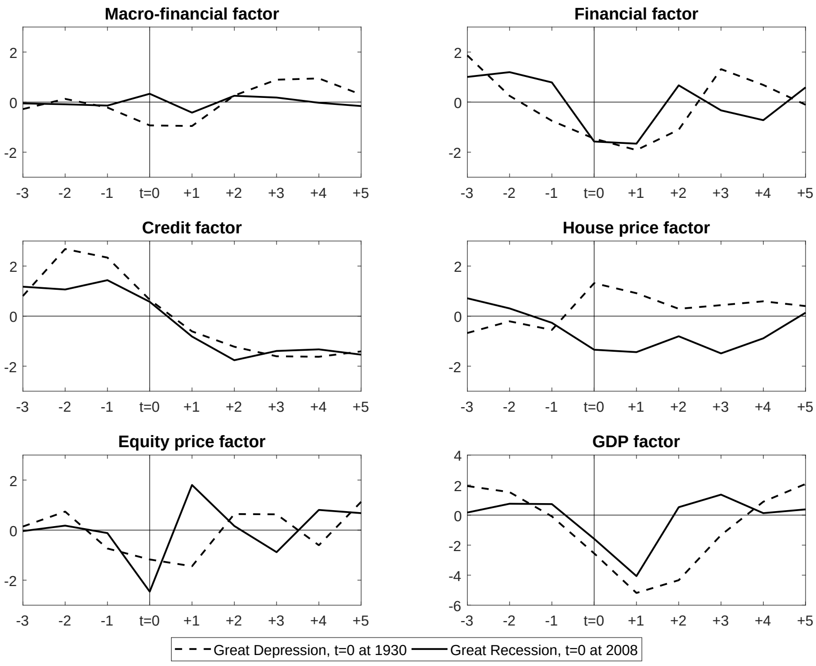

Figure 4: Great Depression vs. Great Recession, Estimated Global Factors.

For the post-war period, we observe rather short-lived fluctuations in most factors during the 1950s and a recession in the global GDP cycle (”Eisenhower Recession” 1958). Apart from that, most factors are rather flat and show only short and small cycles until the end of the 1960s, as discussed in section 4.1.2. This reflects the Bretton-Woods era which was characterised by tight capital controls that limited financial fluctuations. During the subsequent era of large oil price shocks, the global equity price cycle shows a very strong drop in 1973-74 that goes hand in hand with a prolonged bust in the financial cycle during the 1970s and a recession in global GDP.

For the period since the 1980s, we observe a strong increase in the length and amplitude of global credit and house price cycles, as as shown in section 4.1.2. This reflects the housing booms of the 1980s in the US, the UK, Australia, Japan and the Nordic countries. The demand for commercial estate grew during that period, driven by structural change towards personal and financial services that was fueled by financial liberalization policies (Ball, 1994). The resulting bust is observed in the factors during the 1990s. Also the housing boom that preceded the global financial crisis and the subsequent busts are clearly captured by the credit and the housing factors, and to a lesser extent by the financial factor. Recalling that since the 1980s the loadings of the credit and housing factor are strongly positive for all countries, these large parallel housing and credit cycles seem to reflect truly global developments that are much different from dynamics observed for the previous 100 years. On the other hand, the global equity price factor operates at a higher frequency and reflects the stock market turbulences 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. While we do not observe common global shocks between macro and financial series over recent periods, spillovers between the two are likely to occur. As such, the GDP factor captures global recessions that accompany some of the financial boom busts such as the early 1990s recession, the 2001 and the 2008-2009 recessions.

Relation to existing literature. Our results replicate within a unified framework various stylised facts known from existing studies, most of which consider shorter samples and focus either on slow-moving variables such as credit or house prices only, or instead on financial market data such as equity prices.

We confirm the results from earlier papers that observe a financial cycle length of 15 to 20 years over recent sample periods, as long as the (domestic) financial cycle is defined in terms of credit and house prices (see, e.g., Claessens et al., 2012; Borio, 2014; Rünstler and Vlekke, 2018; Lang and Welz, 2018).[15] Our finding of time-variation in the cyclical properties of global credit and house prices is in line with Filardo et al. (2018), who, based on a long sample period, find that the domestic US credit cycle became more protracted during the post-War period. At the same time, as described above, our aggregate financial cycle compares closely to the financial factor based on a high number of risky returns by Miranda-Agrippino and Rey (2015). Schüler et al. (2020) emphasize the policy relevance of such aggregate measures, finding that aggregate measures of (domestic) financial cycles perform better in predicting systemic banking crises than Basel III credit-to-GDP ratios for various countries. Instead, we show that *both* aggregate and sector-specific measures prove important to capture financial fluctuations at the global level over a prolonged period. They capture different cycle lengths and different boom-bust episodes either of which can go hand in hand with recessions in global GDP, and thus should not be ignored by researchers and policy makers.

Finally, we find little evidence for common global macro-financial shocks over recent

[15] Our global credit factor compares quite closely to HP-filtered credit-to-GDP measures provided by the Bank for International Settlements for selected countries, as shown in Figure A11 in the appendix. These measures show rather small fluctuations in the 1960s and 1970s, followed by ample and prolonged cycles since the 1980s. During the 1990s, our factor compares to the negative credit gaps in various Nordic countries, including Norway. During the Great Recession, our factor closely compares to the credit gaps of the US and UK. However, the recent bust in our global factor is weaker compared to the one in the US credit gap, as many countries showed weaker declines in credit compared to the US.

decades, although we do observe that not all common dynamics occur simultaneously implying that lagged spillovers might matter. This is in line with Cesa-Bianchi et al. (2018) who find within a factor-augmented PVAR model that the variances in GDP and stock market volatility across countries, respectively, are mostly explained by their own global shocks and domestic shocks, with little interaction between them—although the authors do find that sizable spillovers can occur at lags. Ha et al. (2017), based on a fixed-parameter dynamic factor model over a recent sample period, find no evidence for common macro-financial shocks, but do find spillovers between global financial factors and GDP at lags. Regarding the effects of monetary policy, Jordà et al. (2019) find an increasing role of monetary policy shocks in affecting bileteral cross-country correlations in equity return risk premiums over a historical sample period. Within the time-varying dynamic factor model framework, we leave the analysis of macro-financial and monetary policy spillover effects for future research.

4.2 Importance of Global Co-Movement

We now turn to the question of how relevant these common shocks are for explaining fluctuations in the individual time series relative to idiosyncratic dynamics. We compute the shares of variance in each time series explained by the global factors for each period of time, which gives us a large panel of results on explained variances. We present variance decompositions for each variable, averaged over the total sample period as well as over five sub-samples. Table 3 distinguishes explained variance shares by factor types and shows credibility sets, summarizing the results across countries. Figure 5 shows the shares of explained variance for selected countries and for country groups: the UK, the US, Continental Europe, Nordic Europe (Denmark, Sweden, Norway, Finland) and Others (Australia, Canada, Japan).[16]

In the upper part of Table 3 results averaged over the full sample period are shown. Global co-movement explains considerably large, albeit not predominant shares of fluctuations in financial aggregates and GDP over the long sample period. The share of fluctuations explained by global co-movement is largest for equity prices (about 40 percent) and smallest for credit and house prices (about 20 percent); about 25 percent of fluctuations in long-term interest rates and GDP, respectively, are explained by global factors. The global dynamics in credit and in GDP, are dominated by the respective variable-specific factors. For equity prices, the financial factor plays the most important role, followed by the equity price factor. For house prices, all three types of factors are equally important, whereas global dynamics in long-term interest rate are dominated by the macro-financial factor.

How did the role of global factors change over time? The lower panel of Table 3 shows that most variation occurred for equity prices: the importance of global co-movement strongly and steadily increased over time. In the most recent period, more than 50 percent of equity price fluctuations are explained by global factors. This reflects strongly increasing

[16]Figure A12 in the appendix shows more detailed results for each country.

Table 3: Variance explained by factors, averaged over countries.

	Credit	House prices	Equity prices	LT rates	GDP
Full sample					
Macro-fin factor	4 (1;11)	6 (2;14)	2 (0;9)	20 (12;32)	7 (2;16)
Financial factor	5 (1;13)	5 (1;12)	24 (13;36)	3 (1;8)	-
Var-specific factor	12 (4;25)	7 (2;16)	11 (6;18)	3 (1;9)	18 (10;29)
Total	**21 (7;48)**	**17 (5;42)**	**37 (20;63)**	**26 (13;49)**	**25 (12;46)**
Sub-samples					
1880-1913					
Macro-fin factor	7 (3;16)	8 (3;18)	3 (0;12)	21 (12;33)	9 (3;19)
Financial factor	6 (1;15)	4 (1;13)	15 (5;29)	5 (1;12)	-
Var-specific factor	8 (1;22)	6 (1;16)	5 (1;13)	3 (1;9)	6 (1;17)
Total	**21 (5;53)**	**18 (5;47)**	**23 (7;53)**	**29 (14;54)**	**15 (4;36)**
1923-1938					
Macro-fin factor	5 (2;12)	7 (3;14)	2 (0;8)	22 (13;32)	8 (3;17)
Financial factor	5 (1;12)	4 (1;12)	22 (11;33)	5 (2;11)	-
Var-specific factor	11 (3;24)	6 (1;15)	10 (5;18)	4 (1;10)	17 (10;25)
Total	**21 (7;47)**	**16 (5;40)**	**34 (17;59)**	**31 (16;53)**	**25 (14;42)**
1948-1983					
Macro-fin factor	3 (1;8)	6 (2;12)	2 (0;7)	21 (12;31)	6 (2;14)
Financial factor	5 (1;12)	4 (1;11)	27 (17;38)	2 (0;5)	-
Var-specific factor	13 (5;25)	7 (2;15)	14 (9;20)	3 (0;9)	22 (12;34)
Total	**21 (7;45)**	**17 (5;38)**	**42 (25;65)**	**25 (12;46)**	**28 (13;48)**
1984-1999					
Macro-fin factor	2 (0;7)	4 (1;11)	2 (0;7)	18 (9;31)	5 (1;14)
Financial factor	5 (2;11)	5 (2;12)	32 (21;43)	1 (0;3)	-
Var-specific factor	15 (7;26)	8 (3;17)	15 (10;23)	2 (0;7)	28 (16;41)
Total	**22 (9;44)**	**18 (6;40)**	**49 (31;73)**	**21 (9;41)**	**33 (17;55)**
2000-2013					
Macro-fin factor	2 (0;8)	4 (1;12)	2 (0;7)	18 (8;31)	5 (1;15)
Financial factor	5 (1;11)	6 (2;13)	34 (23;46)	1 (0;3)	-
Var-specific factor	16 (7;28)	9 (3;20)	16 (10;25)	2 (0;8)	31 (18;45)
Total	**22 (8;47)**	**19 (6;44)**	**52 (33;78)**	**20 (8;42)**	**36 (19;60)**

Notes: Shares of fluctuations explained by factors, in percent. Averaged over 17 countries and over the total sample period (or over sub-samples). Medians over 500 retained Gibbs draws, 68% credible sets in brackets.

roles both of the financial factor and the equity price factor, explaining 34 percent and 16 percent of equity price fluctuations in the recent period, respectively. Strikingly, Figure 5 additionally shows that global factors became more important for equity prices in all countries and country groups in our sample. In some countries, such as the UK, more than 60 percent of equity price fluctuations are due to global factors in the most recent sub-sample.

For the other financial aggregates, the role of global factors remains rather stable over time—at least on average across countries. However, for credit and house prices, the aggregate results mask important heterogeneity across countries. In the US, UK and the Nordic countries global co-movement becomes more important for credit and house prices over time. This is driven both by the financial factor and the respective variable-specific factor. By contrast, in Continental Europe and in the remaining economies, particularly

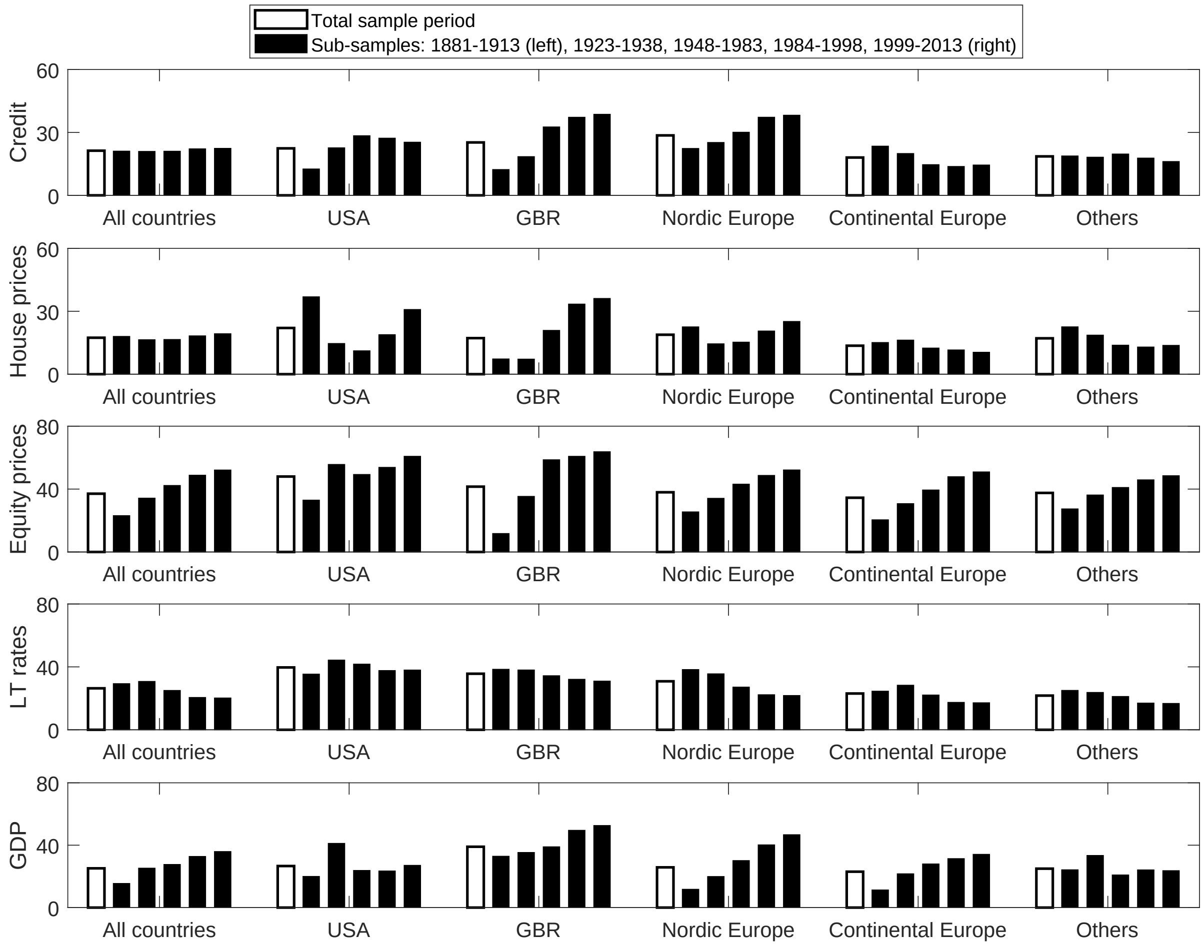

Figure 5: Total variance explained by global factors, by countries and country groups.
Notes: Share of fluctuations explained by global factors (macro-financial factor, financial factor and respective variable-specific factor), in percent. Medians over 500 retained Gibbs draws. White bars show the explained variance shares averaged over the total sample period, black bars show averages over the sub-samples 1881-1913, 1923-1938, 1948-1983, 1984 to 2013 (from left to right). All countries: average over 17 countries (14 countries for house prices). Nordic Europe: Denmark, Finland, Norway, Sweden. Continental Europe: Belgium, France, Germany, Switzerland, as well as (except for house prices) Italy, Portugal and Spain. Others: Australia, Canada, Japan.

Japan, the role of global factors stays stable or even declines over time.[17] To obtain this result, allowing for cross-country differences in the tole of global factors via time-varying loadings and explicitely modeling time-variation in the size of global shocks is essential.[18]

For GDP, we see a strong increase in the role of global co-movement over time. In the most recent sub-sample, 36 percent of GDP fluctuations are due to global dynamics. Back in the early era of financial globalization, the role of the macro-financial factor was more dominant, but only 15 percent of fluctuations in total were due to global dynamics. The

[17]In particular, the role of global factors remains stable or even declines for credit and house prices in core Euro area countries, i.e. Germany, France, Netherlands, Belgium, as well as in Switzerland. By contrast, credit in Spain, Italy, and Portugal becomes more susceptible to global dynamics.

[18]When instead looking at financial co-movement using simple bilateral correlations, where we do not account for cross-country differences and use sample splits to assess time variation, we find that the role of global factors in explaining credit and house price fluctuations increased globally over time (see Table A3 in the appendix).

increase over time occurred for most countries in the sample, although for the United States and Canada, global dynamics in GDP were most dominant during the inter-war period and remained at stable, lower levels thereafter.

Behind the time-variation in explained variance shares lie the parameters of the model, i.e. the time-varying loadings and the stochastic volatilities (Figures A7 to A9, A13 to A14 in the appendix). According to our model, the role of global dynamics increased for equity prices in all countries because, on the one hand, the size of global equity price shocks increased marginally significantly and, on the other hand, the susceptibility of most equity price series to global equity price shocks and global financial shocks rose. Also for GDP, both the size of global GDP shocks and the susceptibility of most countries to these shocks increased over time. 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. Finally, we observe strong decline in the size of macro-financial shocks that is most steep after World War II, but slows down towards the end of the sample period. The macro-financial factor seems to mainly capture the high volatility period during the early era of financial globalization and the Great Depression, but the decline in its volatility might also reflect changes in the quality of the data.

Overall, we observe that equity prices are 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. On the other hand, we observe cross-country differences for credit and house prices. On these markets, the degree of a country's susceptibility to global forces might depend to a larger extent on domestic institutional characteristics and the interconnectedness of the domestic banking sector. In the following subsection, we investigate the role of country characteristics more formally via panel regressions.

4.3 Role of country characteristics

There are two results from the analysis based on the dynamic factor model that merit further investigation. On the one hand, we observe unprecedentedly protracted and ample global cycles in credit and housing starting in the 1970s, but on the other hand, the importance of these cycles has increased for a sub-group of countries only. Therefore, we finalise our analysis by investigating the association between country characteristics and the susceptibility to global factors within a panel regression setting. The aim is to provide more structured insights on the cross-country heterogeneity that we observe: does it correlate with specific country characteristics such as financial openness and integration, financial development, or the exchange rate regime? Comparable analyses have been done by Arregui et al. (2018), Chudik et al. (2018), and Monnet and Puy (2019).

We estimate k panel regressions of the form

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

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, equity prices, house prices, and GDP}. 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.[19]

- $X_{i,t}^{FinInt}$ 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. We include the shares of liquid liabilities to GDP, private credit to GDP, private mortgage lending to GDP, and stock market capitalization as measures of financial market size. The former is a broad indicator of the degree of financial intermediation; it covers banks as well as non-bank financial institutions and lending across sectors (Beck et al., 2010). The other three measures instead capture more specific types of financial intermediation: those via domestic credit, those specifically related to mortgage markets, and those via equity. Additionally, we include the stock market turnover ratio, i.e. the value of traded stock market shares relatively to the value of listed shares, which is typically used as a measure of liquidity of stock markets and financial efficiency.
- $Z_{i,t}$ 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.

All explanatory variables—except for the capital control dummy, the capital account openness index, and the fixed exchange rate dummy—enter in logs.[20] The main data sources are the Macrohistory database and the World Bank Global Financial Development database. We run the estimations over an unbalanced panel over the period 1975 to 2013 and 17 countries.[21] The models are estimated with standard errors robust to heteroskedasticity.

[19]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 endogoneity 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.

[20]We opt for a specification in logs because the dependent variables evolve smoothly, whereas most of the explanatory variables are much more volatile. With the log-log specification we linearise exponential growth patterns and reduce the impact of outliers and strong variations. The coefficients will represent percentage changes. We thus assume that the effects of e.g. financial integration or financial development weigh relatively more on global co-movement when starting out at low levels. Similar specifications were used by Svaleryd and Vlachos (2002) and Giovanni and Levchenko (2009).

[21]Details on data sources and definitions are provided in Table A1 in the appendix. The panel covers 14 countries in case of the explained variance shares in house prices.

The standard errors are clustered on the country level, which accounts for the fact that standard errors within one country might not be independent from one another, particularly in presence of potential serial autocorrelation.

The results presented in Table 4 indicate that—in line with what we would expect—a higher degree of financial openness and cross-border interconnectedness of the banking sector, respectively, tends to be associated with a higher susceptibility of an economy to global cycles. In particular, higher capital account openness and a decrease in capital controls are associated with higher explained variance shares in credit and GDP series. With larger amounts of outstanding cross-border loans, credit and equity price dynamics tend to be driven by global cycles to a larger extent.

The association between financial development and the susceptibility to global forces seems to depend on the type of measure and the financial sub-sector to which it refers. A larger financial market per se—in terms of a larger ratio of liquidity to GDP—is associated with a lower impact of global dynamics on credit, equity prices and GDP. Also, the larger the domestic credit market in terms of the private credit to GDP ratio, the lower the effect of global factors on equity prices and GDP. Thus, a large and developed domestic financial sector seems to be less dependent on global dynamics. However, the association between financial development and global factors seems to be reversed when credit is linked with developed mortgage markets. As such, the susceptibility of house prices to global factors relates positively to the credit-to-GDP ratio. A higher mortgage lending ratio is also associated with a higher role of global factors for credit and for GDP. Finally, while the size of stock markets in terms of stock market capitalization seems not to relate to the susceptibility to global factors, the efficiency of stock markets does: equity markets with a high turnover ratio go hand in hand with a stronger impact of global forces on equity prices, credit and house prices. Here, the link between different asset prices and credit becomes evident.

Also the exchange rate regime seems to play a role: pegging the exchange rate against an anchor is associated with a stronger susceptibility of credit and GDP to global dynamics. Although 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). However, the effect is of small size and only marginally significant according to our results, 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 degree of trade openness and economic development play no significant role for global financial co-movement according to our results.[22]

[22] Arregui et al. (2018) conduct a comparable analysis, but consider advanced as well as emerging

Table 4: Panel estimation results.

Variance expl. by global factors in	Credit	Equity pr.	House pr.	GDP
		Financial openness and integration		
Capital controls	-4.84	0.79	-0.64	-4.70
	[1.13]***	[0.60]	[4.46]	[1.19]***
Capital account openness	0.24	-0.02	-0.14	0.11
	[0.07]***	[0.02]	[0.14]	[0.07]
Cross-border lending	0.05	0.02	0.00	0.00
	[0.02]**	[0.01]***	[0.04]	[0.02]
		Financial development		
Credit to GDP	-0.13	-0.04	0.27	-0.34
	[0.09]	[0.02]*	[0.15]*	[0.09]***
Mortgage lending to GDP	0.18	-0.00	-0.14	0.16
	[0.09]*	[0.01]	[0.14]	[0.03]***
Liquidity to GDP	-0.16	-0.05	-0.23	-0.21
	[0.06]**	[0.02]***	[0.22]	[0.07]**
Stock market capitalization	0.00	0.00	-0.05	-0.02
	[0.02]	[0.00]	[0.04]	[0.01]
Stock market turnover	0.03	0.00	0.03	0.02
	[0.01]***	[0.00]	[0.02]*	[0.01] **
		Trade and economic development		
Trade openness	-0.10	0.01	0.10	-0.14
	[0.09]	[0.01]	[0.15]	[0.09]
Exchange rate peg	0.04	0.00	0.03	0.05
	[0.02]*	[0.01]	[0.05]	[0.03]*
GDP p.c.	0.24	-0.00	-0.18	0.13
	[0.22]	[0.04]	[0.32]	[0.19]
Time trend	-0.04	0.01	0.01	-0.00
	[0.01]***	[0.00]***	[0.01]	[0.01]
Time trend, quadratic	0.00	-0.00	-0.00	0.00
	[0.00]**	[0.00]**	[0.00]	[0.00]
No. of observations	548	548	465	548
No. of countries	17	17	14	17
R^2 adj.	0.53	0.88	0.18	0.66

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.

Overall, financial openness and financial integration are associated with a larger role of global factors for domestic financial markets. With respect to financial development, a larger domestic credit sector per se goes hand in hand with a lower role of global dynamics. But when credit is linked with highly developed asset markets, they might actually enhance the role of global dynamic via mortgage lending and a high stock market turnover.

economies and a shorter sample period. They also find that the sensitivity of domestic financial condition indices to global financial shocks increases with financial integration and openness and declines with financial development. They do find a positive role for trade openness, but they argue that this might reflect omitted indirect financial linkages which should be more relevant than trade links.

4.4 Sensitivity analysis

In this section, we discuss a number of sensitivity checks to alternative specifications of our model. In particular, we focus on specifications with alternative factor structures and on alternative prior choices regarding the time variation in the parameters.[23]

4.4.1 Alternative Factor Structures

We experiment with alternative factor structures, starting with smaller and simpler models and moving to more complex models, in order to check the sensitivity of our results to the choice of the factor structure, and to evaluate in how far there is a gain from choosing a multi-level factor structure with three levels. We begin with a simple one-level model which allows for a single global financial factor, but no asset-specific factors. Next, we estimate a one-level model with asset-specific financial factors (and, optionally, a GDP factor), but no global financial factor. Then, we move to a two-level model with financial variables that has both a global financial factor and asset-specific factors, but does not include a macro-financial factor. Finally, we experiment with three-level models that additionally include bilateral global factors measuring linkages between two variables at a time, such as a credit-house price factor and a credit-GDP factor. Selected results are shown in Figures A15 and A16 in the appendix.

The one-level model with variable-specific cycles provides a credit and a house price factor that are similar to the baseline. However, the equity price factor does not capture short cycles as in the baseline, but rather medium frequency cycles that are covered by the financial factor in the baseline. Thus, the multi-level structure helps capturing cycles of different frequencies across the different financial variables. In the two-level model, factors look very similar to the baseline. Furthermore, we find that the shares of fluctuations explained by the factors are larger in the baseline compared to one-level models with a single aggregate financial factor or with asset-specific factors only, and also somewhat larger compared to two-level models particularly for house prices. The finding that the role of global cycles increased over the historical time span for equity prices is robust across the different specifications, but the increase is somewhat less pronounced in the one-level model. As in the baseline, for the smaller models, we find less variation over time for the other financial aggregates compared to equity prices. Models that additionally include bilateral

[23] We also conducted additional sensitivity analyses, for which results remained robust and are available upon request. For instance, we experimented with alternative models, where we left out one of the variables at a time (e.g. long-term interest rates, GDP) or, alternatively, added CPI as additional variable. We also ran the model from 1950 onward, thus excluding the early era of globalization, the Great Depression and the World Wars altogether. The results look very similar compared to using the whole sample, although a specification without the macro-financial factor makes more sense and yields similar results, given that the macro-financial factor hardly shows any fluctuations after 1950. Hence, the decline in volatility in the factor with the highest level of aggregation might indeed reflect changes in the quality of the data before and after WWII as conjectured above. Finally, our results remain very similar when we exclude one country at a time from the analysis.

factors exhibit time-varying explained variance shares that are similar to the baseline; when adding a credit-house price factor, this factor is significant, but the credit factor and the house price factor turn insignificant.

4.4.2 Sensitivity to Prior Choice

The prior choice regarding the amount of variation in the time-varying parameters can be relevant for the changes over time that we observe. In the baseline, we allow for two types of variation over time: in loadings and in stochastic volatilities. Here, we experiment with shutting down each type of time-variation at a time, or jointly (i.e. imposing fixed parameters). Selected results are shown in Figures A17 and A18 in the appendix.

The global factors stay mostly robust across prior choices. One notable exception is the house price factor, where models without variation in stochastic volatility—given that they restrict the size of global house price shocks to stay constant—fail to produce the long, pronounced cycles observed in the baseline since the 1970s. In the fixed parameter model, the house price factor even remains insignificant and close to zero throughout. Also for the GDP factor, the size of many recessions is smaller when restricting stochastic volatilities to be constant. The shares of fluctuations in the data on average across countries remain roughly similar across prior choices, although less changes over time are observed when we shut down one type of time variation, and obviously no changes over time are observed when we shut down both. The result that the role of global cycles increases over time for equity prices, but not for the other financial aggregates, prevails when shutting down one type of time variation. Not surprisingly, however, for the model with fixed loadings, we do not observe differences across country groups regarding the role of global factors for credit and house prices as we did in the baseline. Regarding the different types of global factors, the role of the macro-financial factor remains rather constant at a high level when we do not allow for changes in stochastic volatility.

We also experiment with a wider range of priors, where we allow for different degrees of parameter variation compared to the baseline. Results stay robust when decreasing or increasing the amount of variation in both loadings and stochastic volatilities somewhat. However, allowing for stronger variations in stochastic volatility only, goes at the expense of receiving less time-variant loadings. For prior choices that are substantially more diffuse or allow for considerably larger fluctuations of the parameters, the model has difficulties to distinguish the variation in the loading parameters from the fluctuations in the factors.

5 Conclusion

We have 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, to which we have brought more than 130 years of data. We provide two main takeaways. First, we find that one financial cycle is not sufficient to explain global co-movement. In fact, both an aggregate financial cycle across financial sectors as well as variable-specific cycles with different cycle lengths are important to explain global fluctuations. Second, global co-movement explains considerable shares of fluctuations in financial aggregates. This is particularly true for equity prices, where global cycles explain more than half of the fluctuations and their role continuously and broadly increased over the long sample period. For credit and house prices, the role of global cycles is overall lower, but this masks pronounced differences across countries: the role of global dynamics increased in the US, the UK and in Nordic economies, but remained constant or declined in most continental European countries and Japan.

Our results bear important policy implications. Policy makers should carefully monitor both composite indices and individual financial sectors in order to detect potential instabilities or materializing global crisis risk. The role of global forces is most pronounced for equity markets, but it can amplify in times when global equity price booms coincide with global credit and house price booms, possibly enhanced by financial deregulation. When such dynamics in asset prices and credit occur simultaneously, leverage and therefore risks to financial stability might increase substantially. This potentially calls for internationally coordinated macroprudential policy, financial regulation and monetary policy (Rajan, 2015; Cecchetti and Tucker, 2016; Gopinath, 2017). At the same time, the complex behaviour of global financial cycles, with co-movement occurring across different aggregates, at different frequencies and evolving 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, as well as the establishment of safety nets that enhance financial stability. Country characteristics, such as the degree of financial openness, can serve as an important criterion to evaluate the relevance of financial stabilization policies or the need for coordination of policies across countries and sectors.

The historical perspective combined with a flexible factor model provide a comprehensive picture regarding the extent of different types of global co-movement of financial variables and GDP and changes over time. At the same time, the analysis pinpoints the need for future research, for instance regarding the drivers of global cyclical fluctuations such as cross-country capital flows, monetary policy or risk perceptions in centre economies from a historical perspective. Addressing such questions requires overcoming various challenges related to data quality and availability and identification in a historical context, which we leave to future research.

References

Almunia, M., A. Benetrix, B. Eichengreen, K. H. O'Rourke, and G. Rua (2010). From Great Depression to Great Credit Crisis: similarities, differences and lessons. *Economic Policy 25*(62), 219–265.

Arregui, N., S. Elekdag, G. Gelos, R. Lafarguette, and D. Seneviratne (2018). Can countries manage their financial conditions amid globalization? IMF Working Paper 18/15.

Ball, M. (1994). The 1980s property boom. *Environment and Planning A: Economy and Space 26*(5), 671–695.

Banbura, M., D. Giannone, M. Modugno, and L. Reichlin (2013). Now-casting and the real-time data flow. *Handbook of Economic Forecasting 2*(Part A), 195–237.

Beck, T., A. Demirgüç-Kunt, and R. Levine (2010). Financial institutions and markets across countries and over time: The updated financial development and structure database. *The World Bank Economic Review 24*(1), 77–92.

Bekaert, G. and A. Mehl (2019). On the global financial market integration "swoosh"? and the trilemma. *Journal of International Money and Finance 94*, 227–245.

Berger, T. and J. Richter (2017). What has caused global business cycle decoupling: Smaller shocks or reduced sensitivity? CEGE - Center for European, Governance and Economic Development Research, Discussion Papers, No. 300, January 2017.

Bluwstein, K., M. Buckmann, A. Joseph, M. Kang, S. Kapadia, and Ö. Şimşek (2020). Credit growth, the yield curve and financial crisis prediction: evidence from a machine learning approach. Bank of England Staff Working Paper No. 848.

Borio, C. (2014). The financial cycle and macroeconomics: What have we learnt? *Journal of Banking & Finance 45*, 182–198.

Borio, C. et al. (2019). Macroprudential frameworks: experience, prospects and a way forward. *IFC Bulletins chapters 49*.

Breitung, J. and S. Eickmeier (2016). Analyzing international business and financial cycles using multi-level factor models: a comparison of alternative approaches. In *Dynamic Factor Models*, pp. 177–214. Emerald Group Publishing Limited.

Bruno, V. and H. S. Shin (2015). Cross-border banking and global liquidity. *The Review of Economic Studies 82*(2), 535–564.

Carstensen, K. and L. Salzmann (2017). The G7 business cycle in a globalized world. *Journal of International Money and Finance 73*, 134–161.

Carter, C. K. and R. Kohn (1994). On Gibbs sampling for state space models. *Biometrika 81*(3), 541–553.

Cecchetti, S. G. and P. Tucker (2016, January). Is there macroprudential policy without international cooperation? CEPR Discussion Paper No. 11042.

Cerutti, E., S. Claessens, and A. K. Rose (2017). How important is the global financial cycle? evidence from capital flows. *IMF Economic Review*, 1–37.

Cesa-Bianchi, A., A. Ferrero, and A. Rebucci (2018). International credit supply shocks. *Journal of International Economics 112*, 219–237.

Chinn, M. D. and H. Ito (2006). What matters for financial development? Capital controls, institutions, and interactions. *Journal of Development Economics 81*(1), 163–192.

Chudik, A., J. Koech, and M. Wynne (2018). The heterogeneous effects of global and national business cycles on employment in U.S. states and metropolitan areas. Globalization Institute Working Paper 343, Federal Reserve Bank of Dallas.

Claessens, S., M. A. Kose, and M. E. Terrones (2012). How do business and financial cycles interact? *Journal of International Economics 87*(1), 178–190.

Del Negro, M. and C. Otrok (2008). Dynamic factor models with time-varying parameters: measuring changes in international business cycles. *FRB of New York Staff Report* (326).

Eickmeier, S. and B. Hofmann (2013). Monetary policy, housing booms, and financial (im)balances. *Macroeconomic Dynamics 17*(04), 830–860.

European Central Bank (2018). Real and financial cycles in EU countries: stylised facts and modelling implications. Occasional Paper Series No. 205.

Filardo, A., M. J. Lombardi, and M. Raczko (2018). Measuring financial cycle time. BIS Working Papers No. 755.

Gambacorta, L. and A. Murcia (2017). The impact of macroprudential policies and their interaction with monetary policy: an empirical analysis using credit registry data.

Giovanni, J. d. and A. A. Levchenko (2009). Trade openness and volatility. *The Review of Economics and Statistics 91*(3), 558–585.

Gopinath, G. (2017). Rethinking international macroeconomic policy. Peterson Institute for International Economics, October.

Ha, J., M. A. Kose, C. Otrok, and E. S. Prasad (2017). Global macro-financial cycles and spillovers. Paper presented at the 18th Jacques Polak Annual Research Conference, International Monetary Fund, November 2-3, Washington D.C.

Harding, D. and A. Pagan (2002). Dissecting the cycle: a methodological investigation. *Journal of Monetary Economics 49*(2), 365–381.

Helbling, T., R. Huidrom, M. A. Kose, and C. Otrok (2011). Do credit shocks matter? A global perspective. *European Economic Review 55*(3), 340–353.

Hirata, H., M. A. Kose, C. Otrok, and M. E. Terrones (2012). Global house price fluctuations: Synchronization and determinants. NBER Working Paper No. 18362.

Iacoviello, M. (2015). Financial business cycles. *Review of Economic Dynamics 18*(1), 140–163.

Ilzetzki, E., C. M. Reinhart, and K. S. Rogoff (2019). Exchange arrangements entering the twenty-first century: Which anchor will hold? *The Quarterly Journal of Economics 134*(2), 599–646.

International Monetary Fund (2017). Are countries losing control of domestic financial conditions? *Global Financial Stability Report. Getting the Policy Mix Right*. April 2017, Chapter 3.

Jordà, Ò., M. Schularick, and A. M. Taylor (2015a). Betting the house. *Journal of International Economics 96*, S2–S18.

Jordà, Ò., M. Schularick, and A. M. Taylor (2015b). Leveraged bubbles. *Journal of Monetary Economics 76*, S1–S20.

Jordà, Ò., M. Schularick, and A. M. Taylor (2017). Macrofinancial history and the new business cycle facts. In M. Eichenbaum and J. A. Parker (Eds.), *NBER Macroeconomics Annual 2016*, Volume 31, pp. 213–263. University of Chicago Press.

Jordà, Ò., M. Schularick, A. M. Taylor, and F. Ward (2019). Global financial cycles and risk premiums. *IMF Economic Review 67*(1), 109–150.

Kalemli-Ozcan, S., E. Papaioannou, and F. Perri (2013). Global banks and crisis transmission. *Journal of International Economics 89*(2), 495–510.

Kim, S., N. Shephard, and S. Chib (1998). Stochastic volatility: likelihood inference and comparison with ARCH models. *The Review of Economic Studies 65*(3), 361–393.

Knoll, K., M. Schularick, and T. M. Steger (2017). No price like home: Global house prices, 1870-2012. *The American Economic Review 107*(2), 331–353.

Kollmann, R., Z. Enders, and G. J. Müller (2011). Global banking and international business cycles. *European Economic Review 55*(3), 407–426.

Kose, M. A., C. Otrok, and E. Prasad (2012). Global business cycles: convergence or decoupling? *International Economic Review 53*(2), 511–538.

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), 1216–1239.

Lang, J. H. and P. Welz (2018). Semi-structural credit gap estimation. ECB Working Paper No. 2194.

Meller, B. and N. Metiu (2017). The synchronization of credit cycles. *Journal of Banking & Finance 82*, 98–111.

Menden, C. and C. R. Prõano (2017). Dissecting the financial cycle with dynamic factor models. *Quantitative Finance 17*(12), 1965–1994.

Miranda-Agrippino, S. and H. Rey (2015). World asset markets and the global financial cycle. NBER Working Paper No. 21722.

Monnet, E. and D. Puy (2019). One Ring to Rule Them All? New Evidence on World Cycles. IMF Working Paper 19/202.

Obstfeld, M. (2015). Trilemmas and trade-offs: Living with financial globalisation. BIS Working Paper 2015.

Obstfeld, M., J. C. Shambaugh, and A. M. Taylor (2005). The trilemma in history: Tradeoffs among exchange rates, monetary policies, and capital mobility. *Review of Economics and Statistics 87*(3), 423–438.

Quah, D. and T. J. Sargent (1993). A dynamic index model for large cross sections. In *Business cycles, indicators and forecasting*, pp. 285–310. University of Chicago Press.

Rajan, R. G. (2015). Competitive monetary easing: Is it yesterday once more? *Macroeconomics and Finance in Emerging Market Economies 8*(1-2), 5–16.

Reinhart, C. M., V. Reinhart, and C. Trebesch (2016). Global cycles: Capital flows, commodities, and sovereign defaults, 1815–2015. *The American Economic Review 106*(5), 574–580.

Rey, H. (2015). Dilemma not trilemma: The global financial cycle and monetary policy independence. NBER Working Paper 21162.

Ritschl, A., S. Sarferaz, and M. Uebele (2016). The US business cycle, 1867–2006: A dynamic factor approach. *Review of Economics and Statistics 98*(1), 159–172.

Rünstler, G. and M. Vlekke (2018). Business, housing, and credit cycles. *Journal of Applied Econometrics 33*(2), 212–226.

Schularick, M. and A. M. Taylor (2012). Credit booms gone bust: monetary policy, leverage cycles, and financial crises, 1870–2008. *The American Economic Review 102*(2), 1029–1061.

Schüler, Y. S., P. P. Hiebert, and T. A. Peltonen (2020). Financial cycles: Characterisation and real-time measurement. *Journal of International Money and Finance 100*, 102082.

Stock, J. H. and M. W. Watson (2005). Implications of dynamic factor models for VAR analysis. NBER Working Paper No. 11467.

Stock, J. H. and M. W. Watson (2012). Disentangling the channels of the 2007-2009 recession. NBER Working Paper No. 18094.

Strohsal, T., C. R. Prõano, and J. Wolters (2019). Characterizing the financial cycle: Evidence from a frequency domain analysis. *Journal of Banking & Finance* (forthcoming).

Svaleryd, H. and J. Vlachos (2002). Markets for risk and openness to trade: how are they related? *Journal of International Economics 57*(2), 369–395.

Verona, F. (2016). Time–frequency characterization of the US financial cycle. *Economics Letters 144*, 75–79.

Appendix

Table A1: Variables used in panel analysis.

Variable	Source	Definition	Later data availability
Capital controls	Ilzetzki et al. (2019)	Dummy variable on capital restrictions / unified markets	–
Capital account openness	Chinn and Ito (2006)	Index	NLD 1981, CHE 1996
Cross-border lending	WB GFD	Loans from nonresident banks (amounts outstanding) to GDP	CHE 1980
Credit to GDP	Macrohistory, own calc.	Total loans to non-financial private sector relative to GDP	–
Morgage lending to GDP	Macrohistory, own calc.	Total mortgage loans to non-financial private sector relative to GDP	–
Liquidity to GDP	WB GFD	Ratio of liquid liabilities (M3) relative to GDP	CAN *until* 2008
Stock market capitalization	WB GFD	Total value of all listed shares in a stock market as percentage of GDP	AUS 1979, CHE 1980, FIN 1982, ITA 1989, NOR 1981
Stock market turnover	WB GFD	Total value of shares traded divided by the average market capitalization	
Trade openness	Macrohistory, own calc.	Sum of imports and exports to GDP	–
Exchange rate peg	Macrohistory	Dummy for fixed exchange rate regime	–
GDP p.c.	Macrohistory	Real GDP per capita (PPP)	–

Notes: Macrohistory - Macrohistory database; WB GFD - World Bank Global Financial Development Database; own calc. - own calculations; "–" : data available over full sample period used in panel analysis, 1975 -2013.
Country abbreviations: AUS- Australia, BEL - Belgium, CAN - Canada, CHE - Switzerland, DEU - Germany, DNK - Denmark, ESP - Spain, FIN - Finland, FRA - France, GBR - United Kingdom, ITA - Italy, JPN, Japan, NLD- Netherlands, NOR - Norway, PRT - Portugal, SWE - Sweden, USA - United States.

Table A2: Descriptive statistics: means and standard deviations.

	Credit	Housing	Equity	Int. Rate	GDP
1880-1913	0.04 (0.9)	-0.03 (1.1)	-0.06 (0.5)	0.01 (1.1)	0.04 (0.9)
1923-1938	-0.37 (1.2)	-0.14 (1.0)	0.01 (1.0)	-0.15 (1.4)	-0.27 (1.5)
1948-1983	0.15 (0.9)	0.04 (1.0)	-0.08 (1.1)	0.05 (0.9)	0.21 (0.8)
1984-1998	-0.07 (0.9)	-0.10 (0.8)	0.37 (1.0)	-0.01 (0.4)	-0.1 (0.6)
1999-2013	-0.04 (0.7)	0.14 (0.7)	-0.16 (1.2)	-0.04 (0.3)	-0.14 (0.7)
Total	0 (1)	0 (1)	0 (1)	0 (1)	0 (1)

Notes: Means and standard deviations (in brackets) of the variables used for factor analysis, averaged over 17 countries (14 for house prices) and sub-samples. The data were transformed to growth rates or differences (for long-term interest rates), detrended based on a ± 8 years centered moving window, and standardized.

Table A3: Average bilateral correlations across countries.

	Credit	Housing	Equity	Int. Rate	GDP	Finance	All
1880-1913	0.05	0.00	0.11	0.13	0.03	0.03	0.02
1923-1938	0.17	0.03	0.36	0.35	0.19	0.06	0.05
1948-1983	0.14	0.04	0.24	0.26	0.26	0.07	0.07
1984-1998	0.33	0.28	0.30	0.22	0.35	0.09	0.13
1999-2013	0.37	0.16	0.51	0.49	0.57	0.19	0.19
Total	0.18	0.07	0.32	0.23	0.23	0.08	0.07

Notes: The first five columns refer to bilateral correlations corresponding to each of the five variables, respectively. The two last columns refer to average bilateral correlations across the four financial variables ("Finance") and across all five variables ("All"), respectively. Missing values were linearly extra- and interpolated.

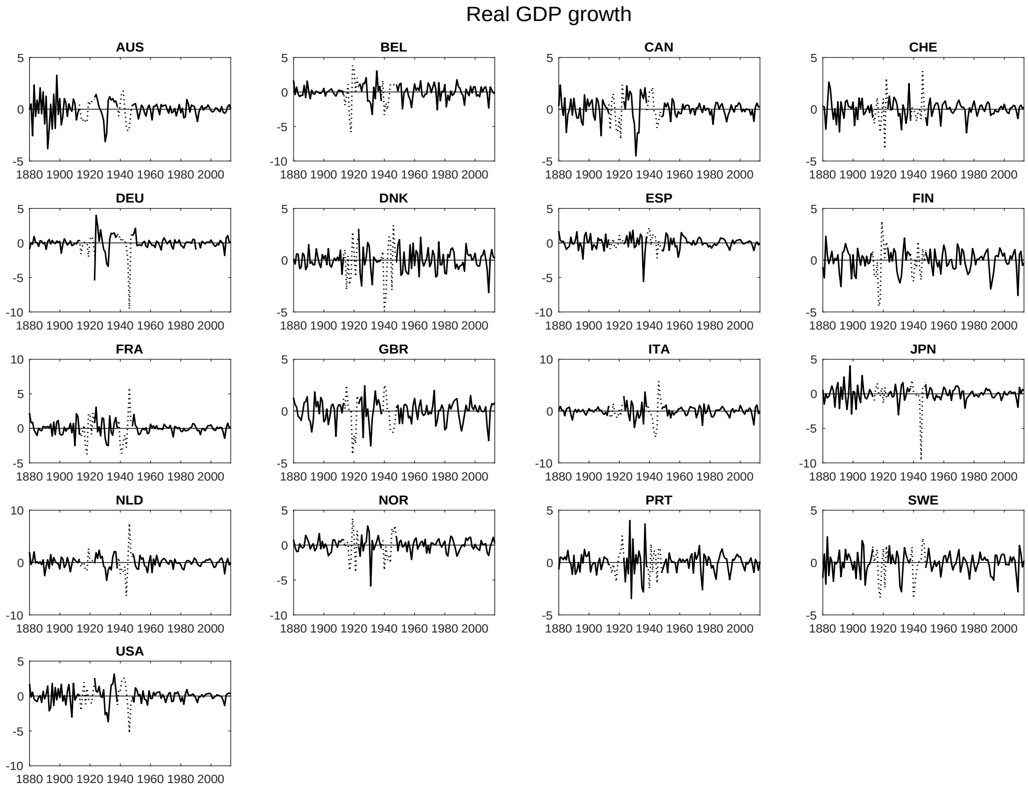

Figure A1: Log real GDP growth.

Notes: Log differenced time series. Growth rates were detrended via a centered moving average of ± 8 years and then standardized. Dotted parts show years around World Wars (1914 to 1922, 1939 to 1947) that were not used in the estimation.

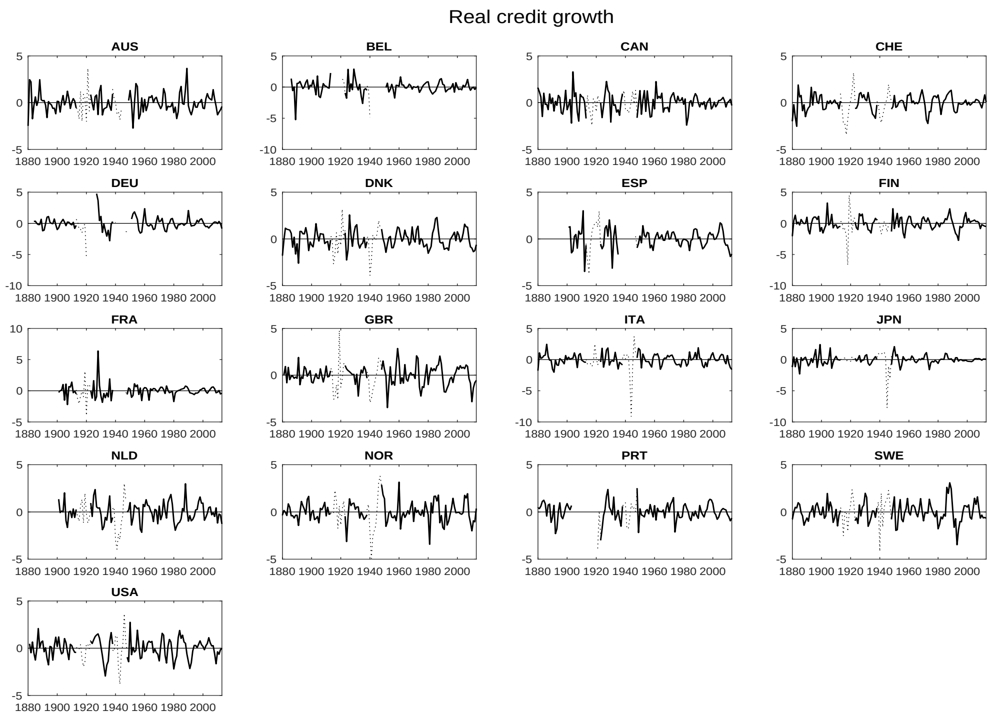

Figure A2: Log real credit growth.

Notes: Log differenced time series. Growth rates were detrended via a centered moving average of ± 8 years and then standardized. Dotted parts show years around World Wars (1914 to 1922, 1939 to 1947) that were not used in the estimation. Empty parts indicate missing values.

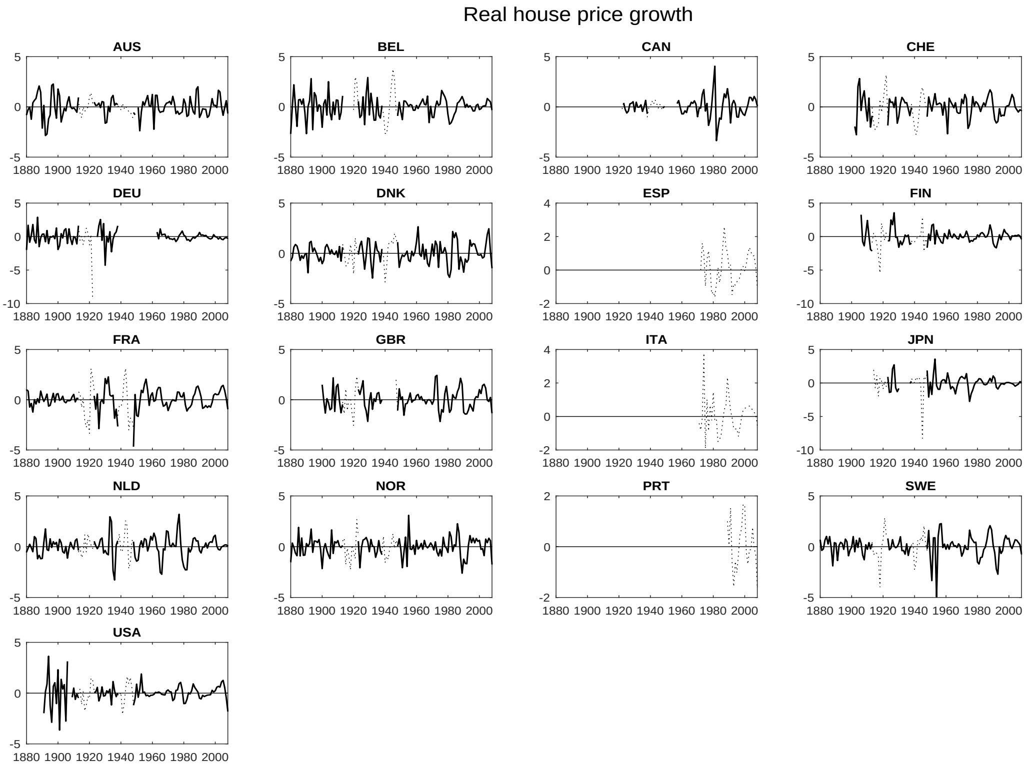

Figure A3: Log real house price growth growth.
Notes: Growth rates were detrended via a centered moving average of ± 8 years and then standardized. Dotted parts show data not used in the estimation: house prices for Spain, Italy and Portugal are not included due to the short available time series. Also see notes of Figure A2.

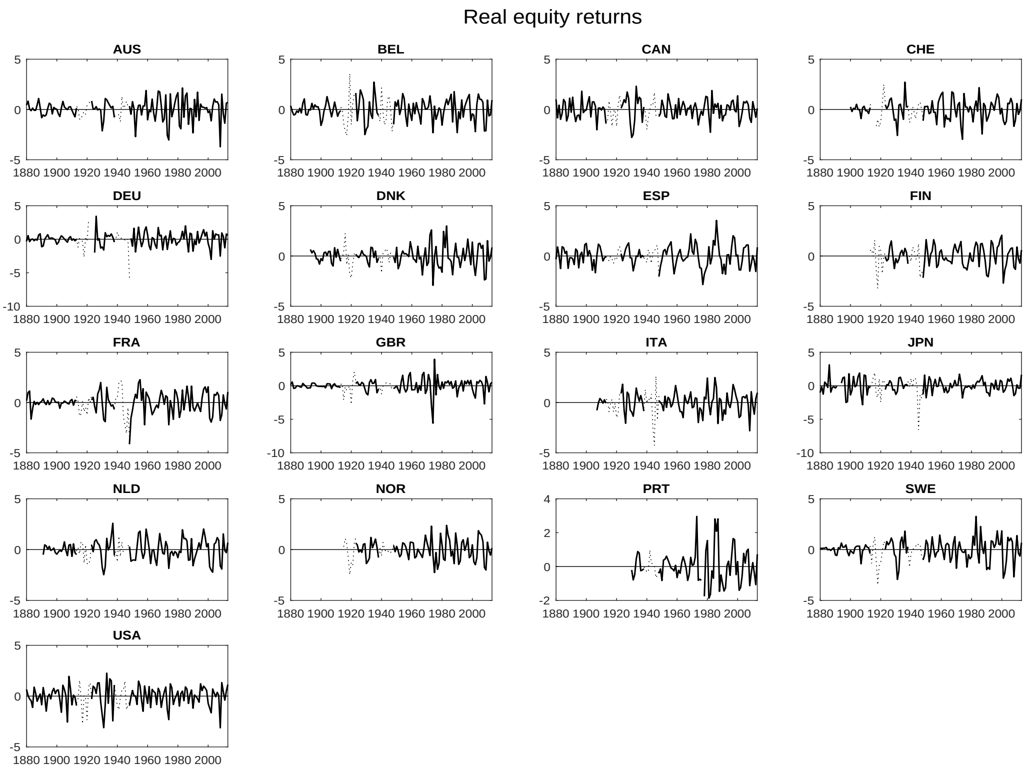

Figure A4: Log real equity returns.
Notes: Growth rates were detrended via a centered moving average of ± 8 years and then standardized. Also see notes of Fig.A2.

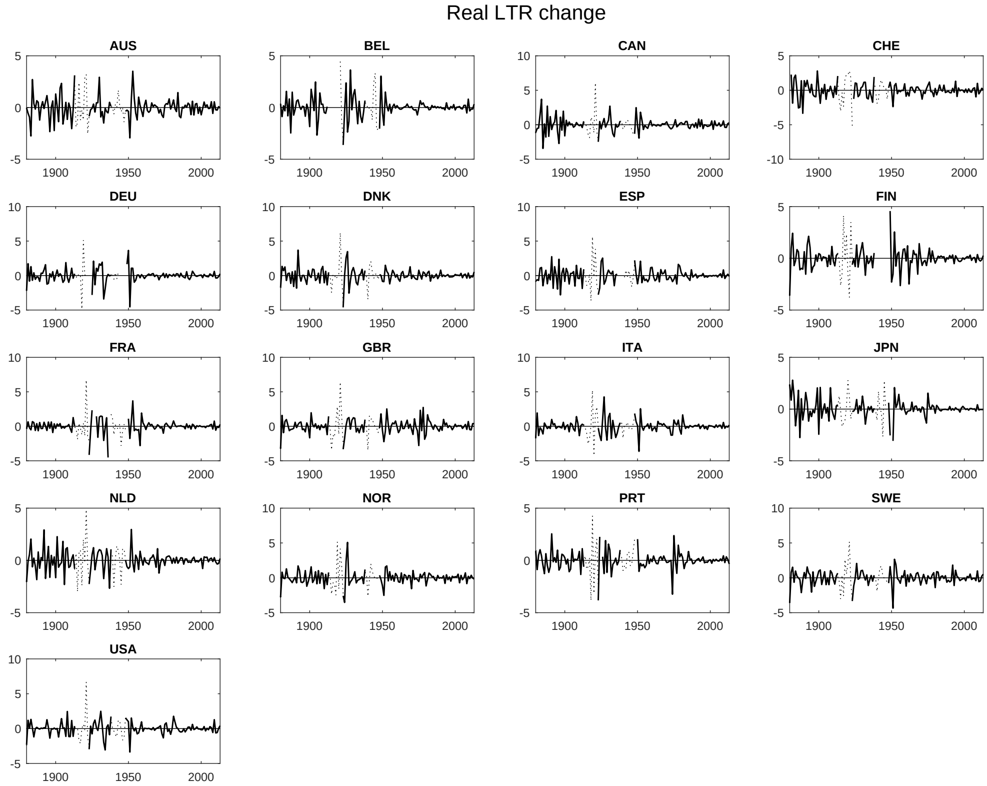

Figure A5: Differenced real long term interest rates.
Notes: Differenced time series were detrended via a centered moving average of ± 8 years and then standardized. Also see notes of Fig.A2.

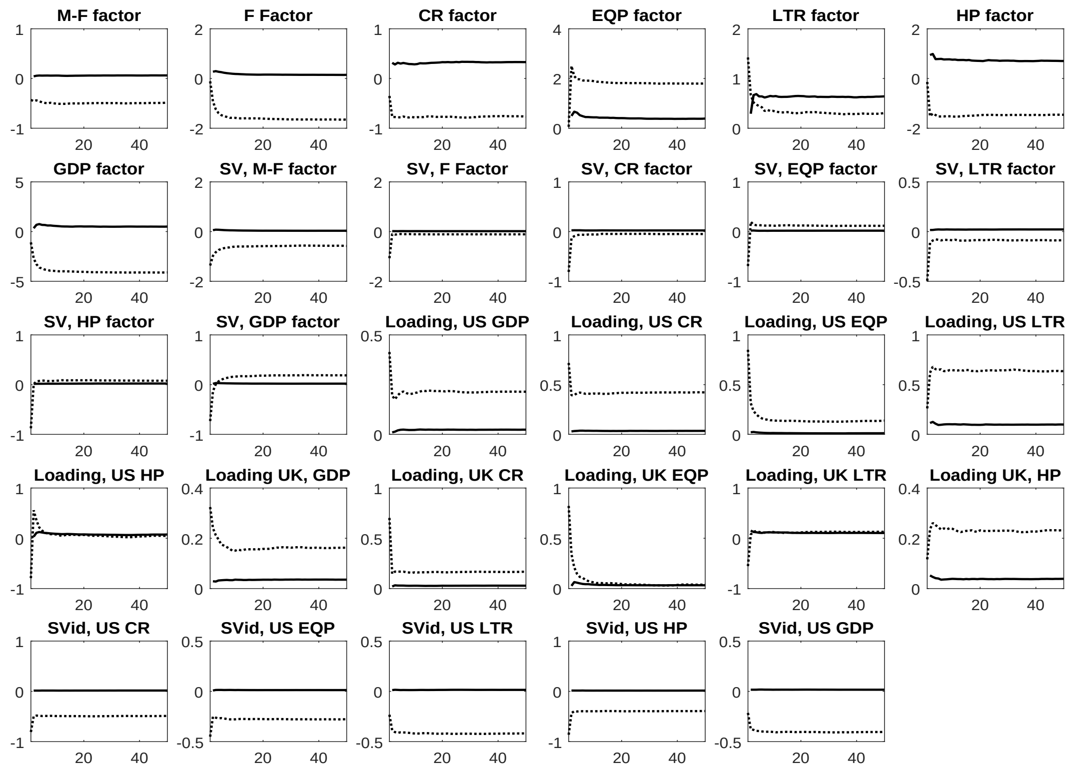

Figure A6: Recursive means and variances of Gibbs sampler draws, selected state variables.
Notes: Dotted lines show recursive means and solid lines show recursive variances of draws, calculated after every 400th draw (i.e. every 8th draw is retained and every 50th time recursive moments are calculated), for the respective state variables at t=2010.

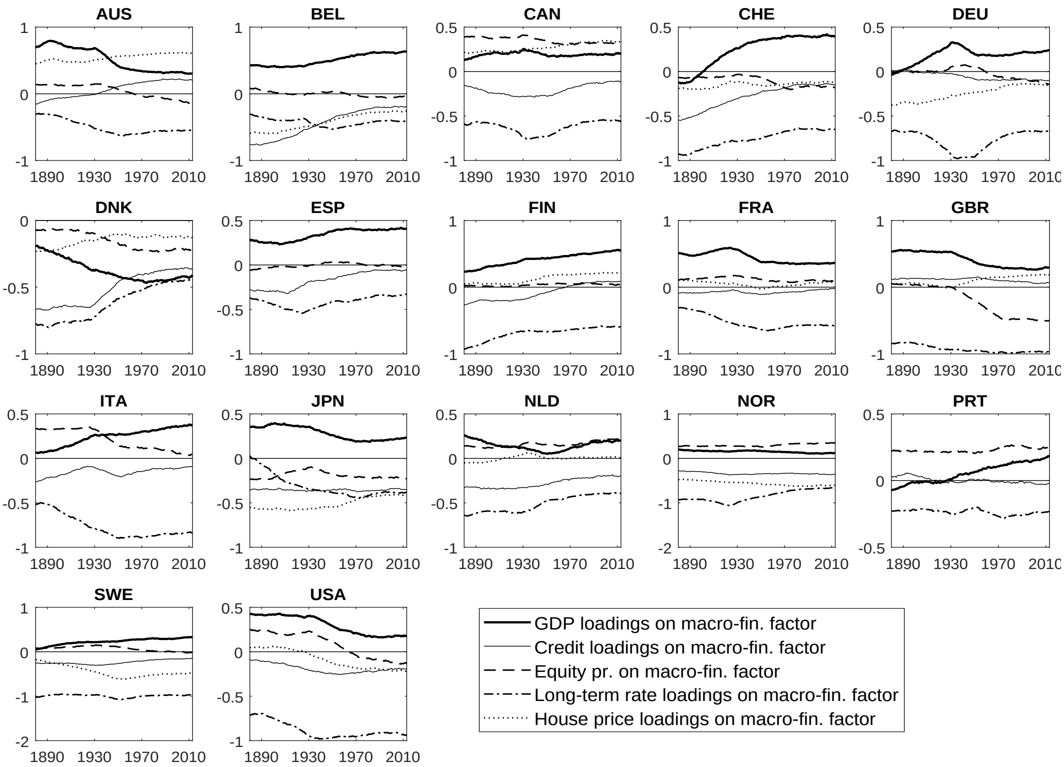

Figure A7: Factor loadings on macro-financial factor.
Notes: Estimated with the multi-level TVP DFM. Credibility sets not presented for readability.

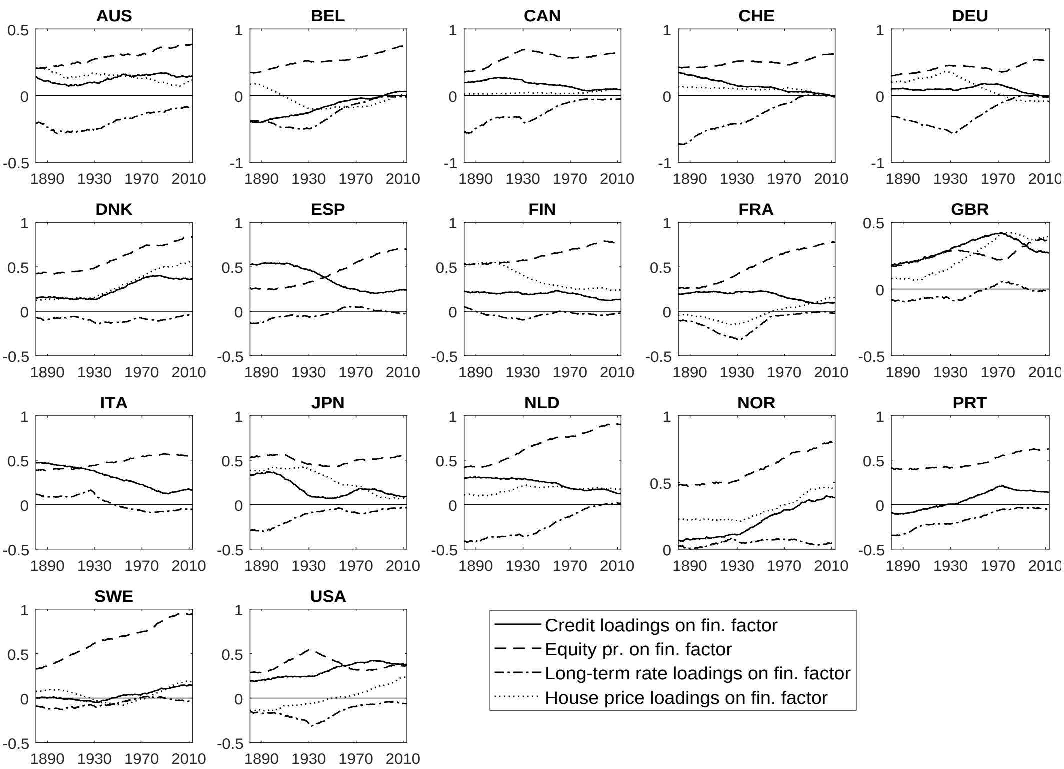

Figure A8: Factor loadings on financial factor.
Notes: Estimated with the multi-level TVP DFM. Credibility sets not presented for readability.

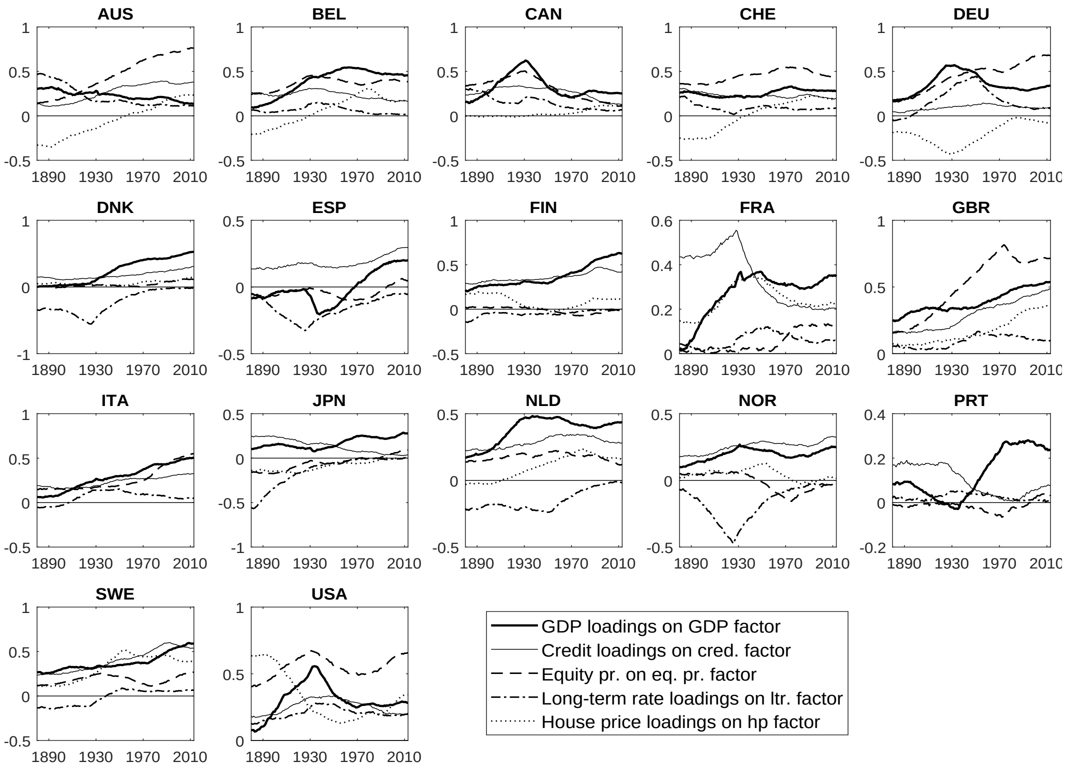

Figure A9: Factor loadings on variable-specific factors.
Notes: Estimated with the multi-level TVP DFM. Credibility sets not presented for readability.

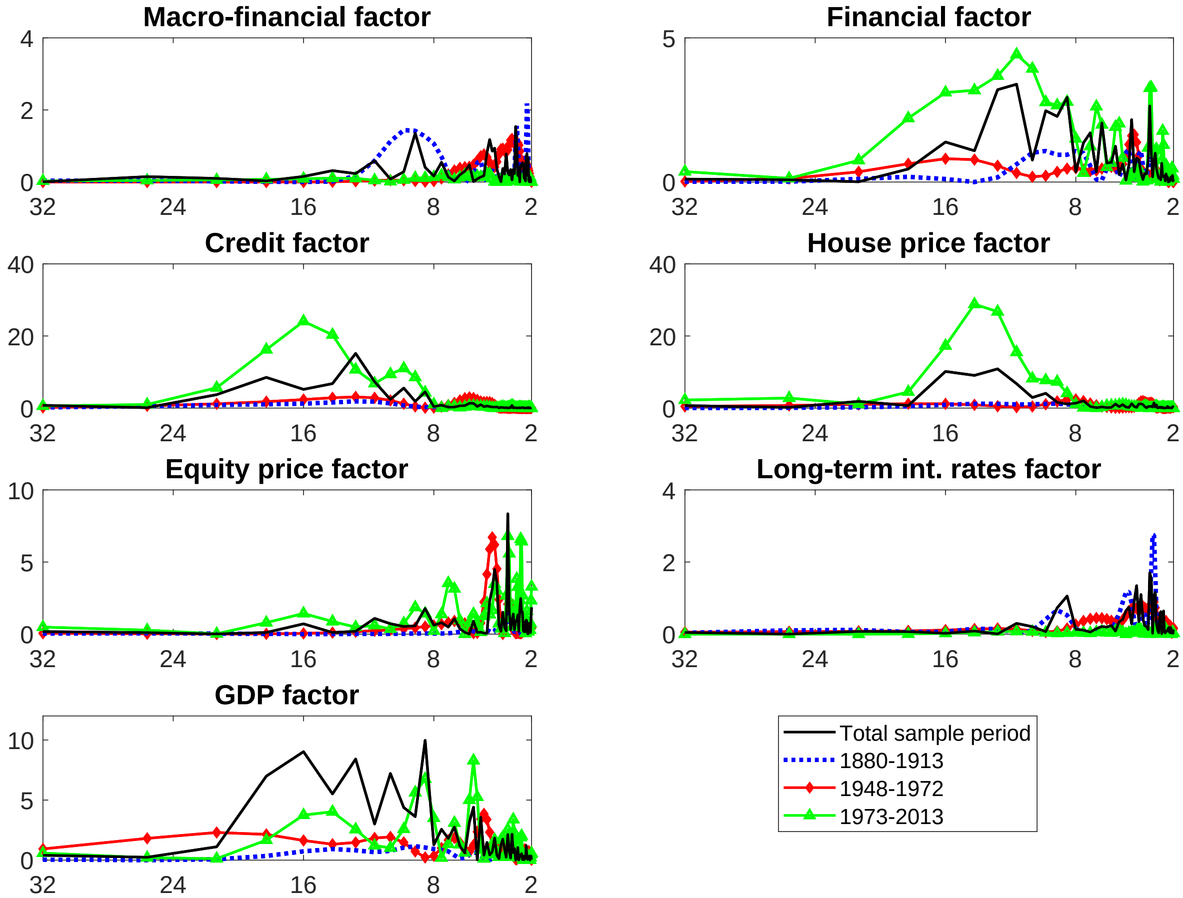

Figure A10: Spectral densities of estimated factors.
Notes: The x-axis measures the length of cycles from 2 years to 32 years. Spectral densities are based on detrended, differenced series and are computed over the total period (black solid lines) and over the sub-samples 1880-1913 (early era, blue dotted lines), 1948-1972 (post-War/Bretton-Woods, red line with diamond markers) and 1973-2013 (post-Bretton-Woods, green line with triangular markers). Spectral densities over the inter-war period are not reported, as some of the densities are very large at medium frequencies and likely to be biased through the exclusion of World Wars.

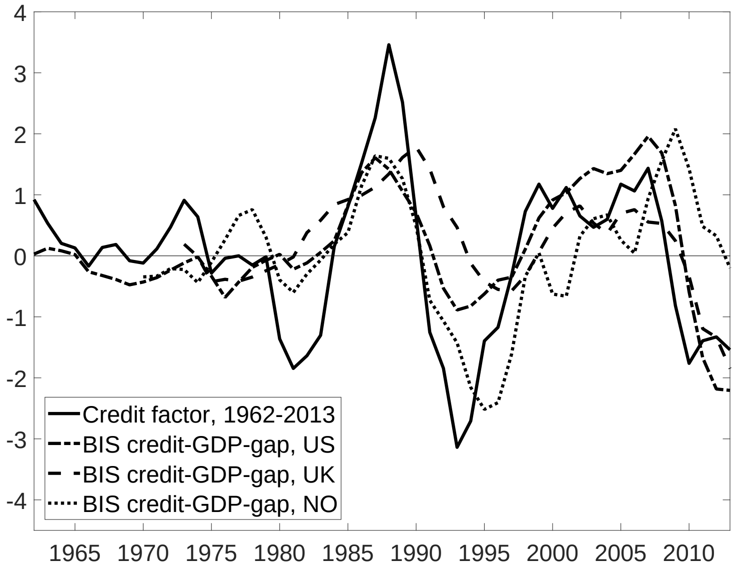

Figure A11: Credit factor vs. credit-to-GDP gaps.

Notes: The right panel compares our global credit factor with HP-filtered credit-to-GDP gaps for the US, UK and Norway provided by the Bank for International Settlements from 1962 onwards. For the comparison, we transformed the credit-to-GDP gaps to an annual frequency and standardized them. Source: Bank for International Settlements, authors' calculations.

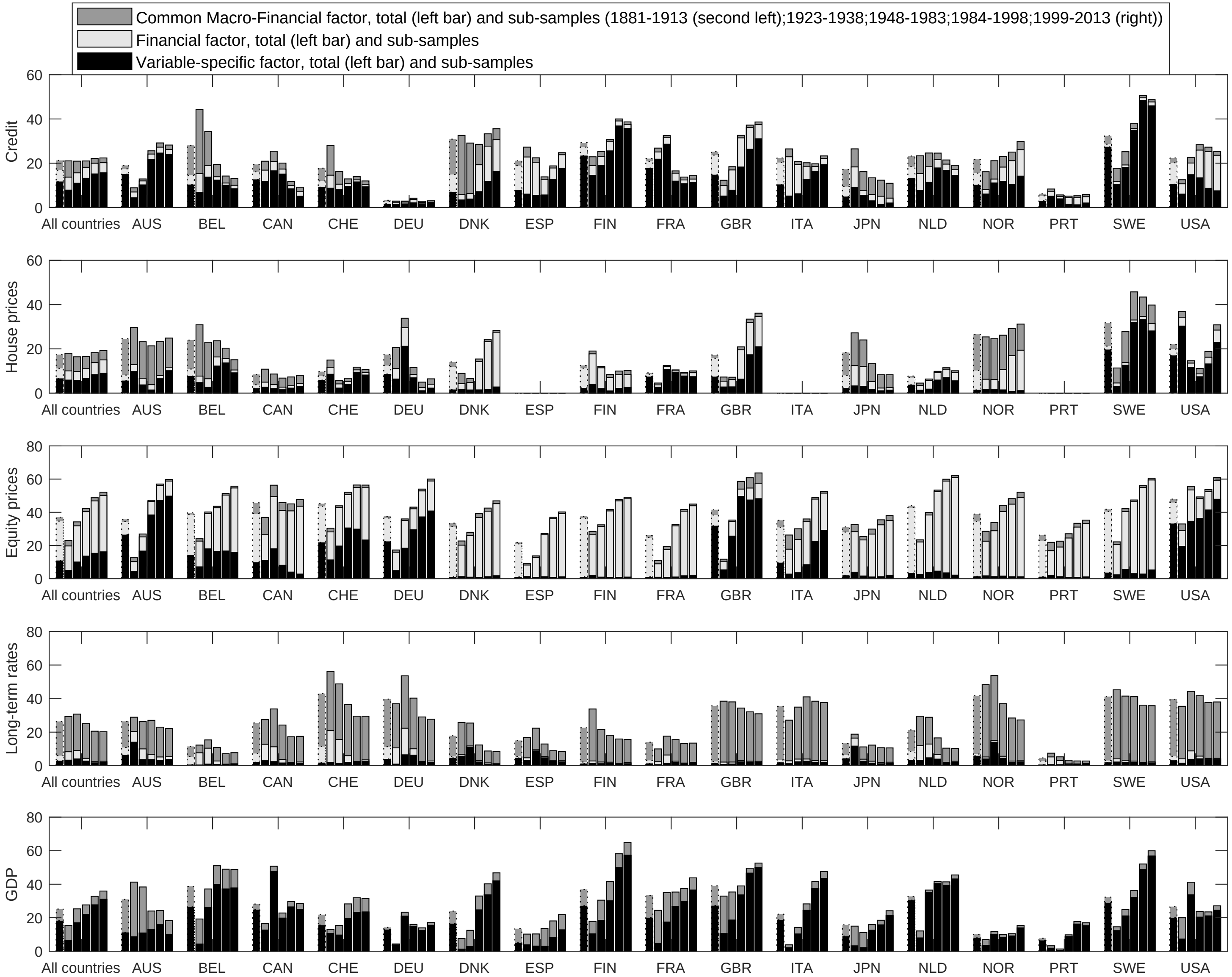

Figure A12: Total variance explained by global factors, by countries and factor type.
Notes: Share of fluctuations explained by global factors (macro-financial factor in dark gray, financial factor in light gray, and respective variable-specific factor in black), in percent. Medians over 500 retained Gibbs draws. Bars at the very left show the explained variance shares averaged over the total sample period, remaining bars show averages over the sub-samples 1881-1913, 1923-1938, 1948-1983, 1984 to 2013 (from second left to right). All countries: average over 17 countries (14 countries for house prices).

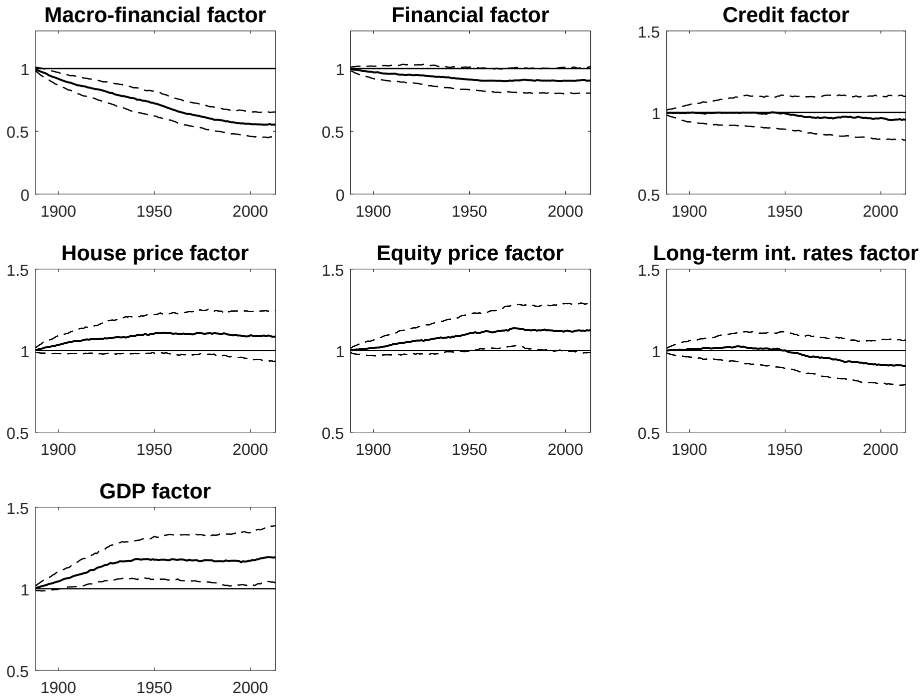

Figure A13: Stochastic volatilities of global factors.
Notes: Solid lines show the posterior median, dashed lines show the 68 percent credible sets.

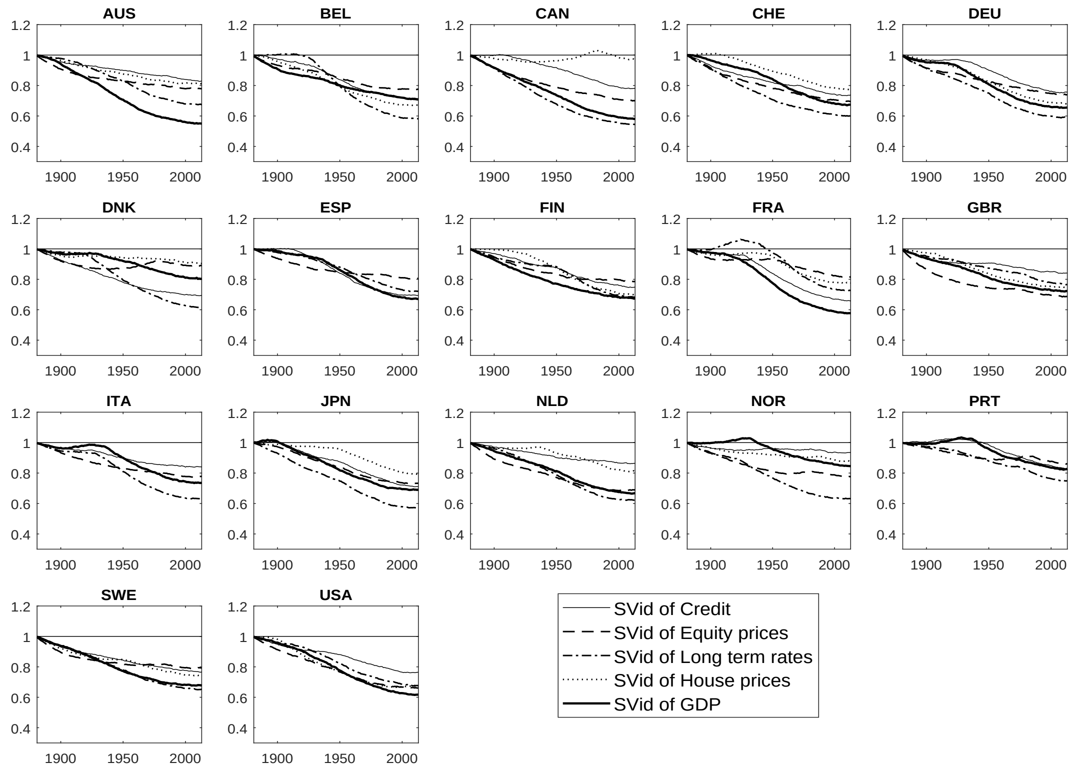

Figure A14: Idiosyncratic stochastic volatilities.
Notes: Estimated with the multi-level TVP DFM. Credibility sets not presented for readability.

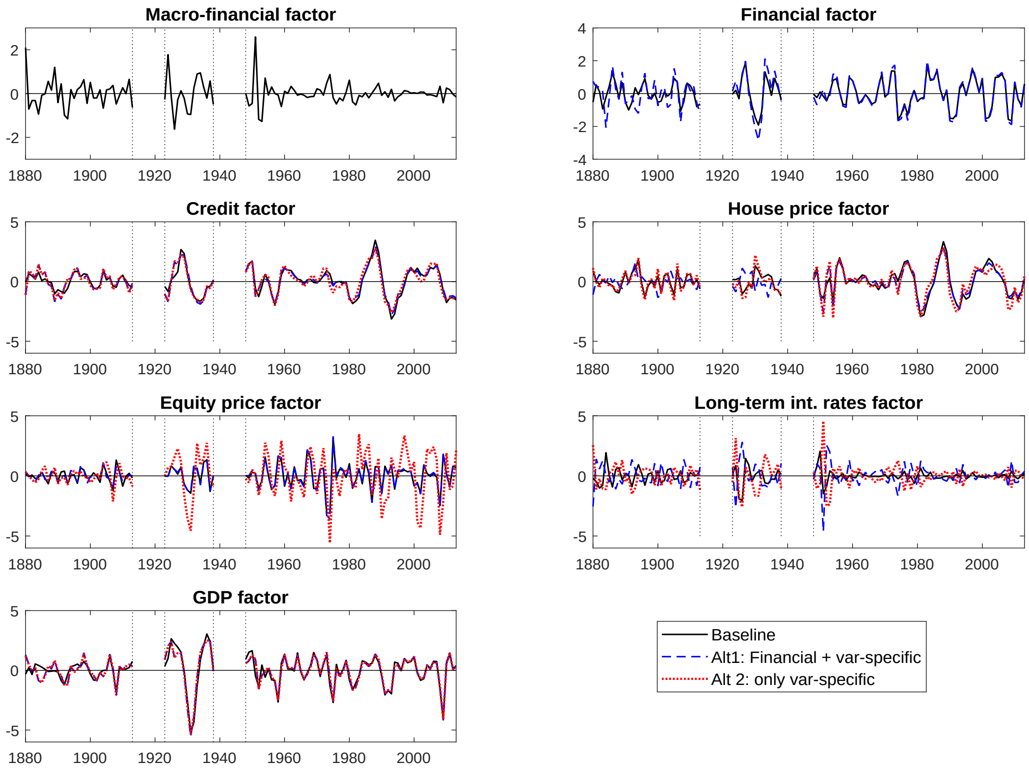

Figure A15: Global factors, sensitivity to alternative factor structures.
Notes: Common factors, medians over 500 retained Gibb draws. Baseline: Baseline, 3-level model with macro-financial factor, financial factor and variable-specific factors. Alt1: 2-level model with financial factor and variable-specific factors. Alt2: 1-level model with variable-specific factors.

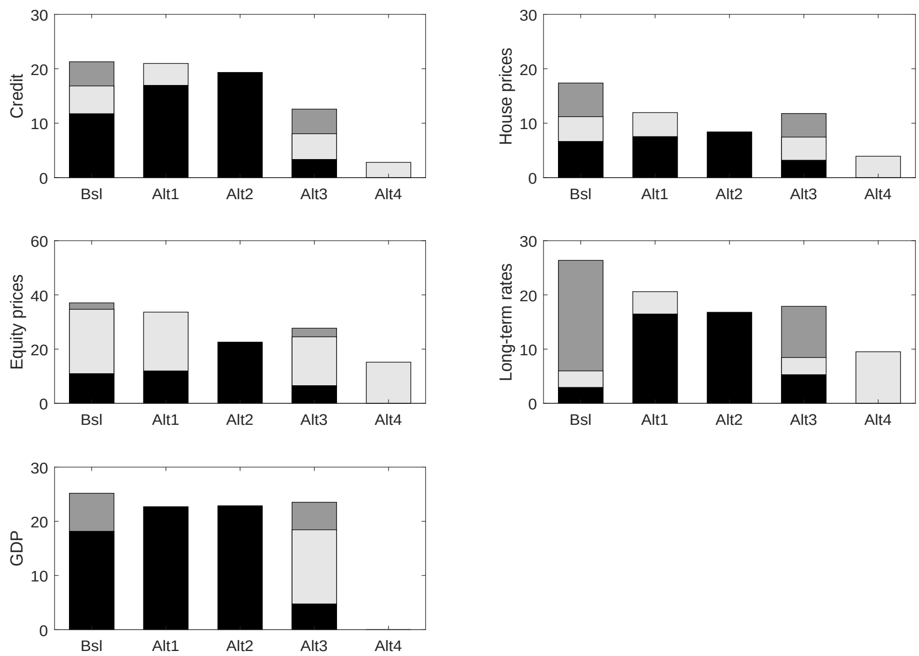

Figure A16: Explained variance shares, sensitivity to alternative factor structures.
Notes: Shares of variances explained by common factors, averaged over time and countries, medians over 500 retained Gibb draws. Bsl: Baseline, 3-level model with macro-financial factor (dark gray), financial factor (light gray) and variable-specific factors (black). Alt1: 2-level model with financial factor (light gray) and variable-specific factors (black). Alt2: Model with variable-specific factors. Alt3: Model with 3 common factors, no factor structure imposed (all variables load on all factors). Alt4: Model with 1 financial factor (all financial variables load).

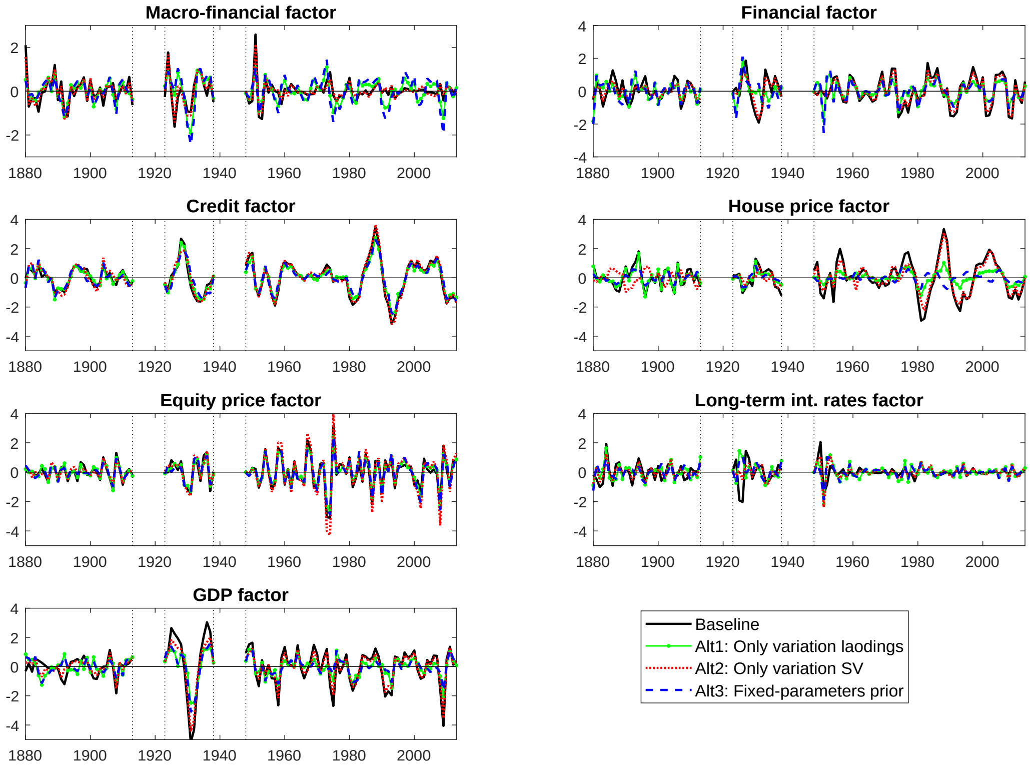

Figure A17: Global factors, sensitivity to alternative prior choices.
Notes: Common factors, medians over 500 retained Gibb draws. Baseline: Model with time-variation in loadings and stochastic volatilities. Alt1: Time-variation in loadings only. Alt2: Time-variation in stochastic volatilities only. Alt3: No time-variation (fixed parameters).

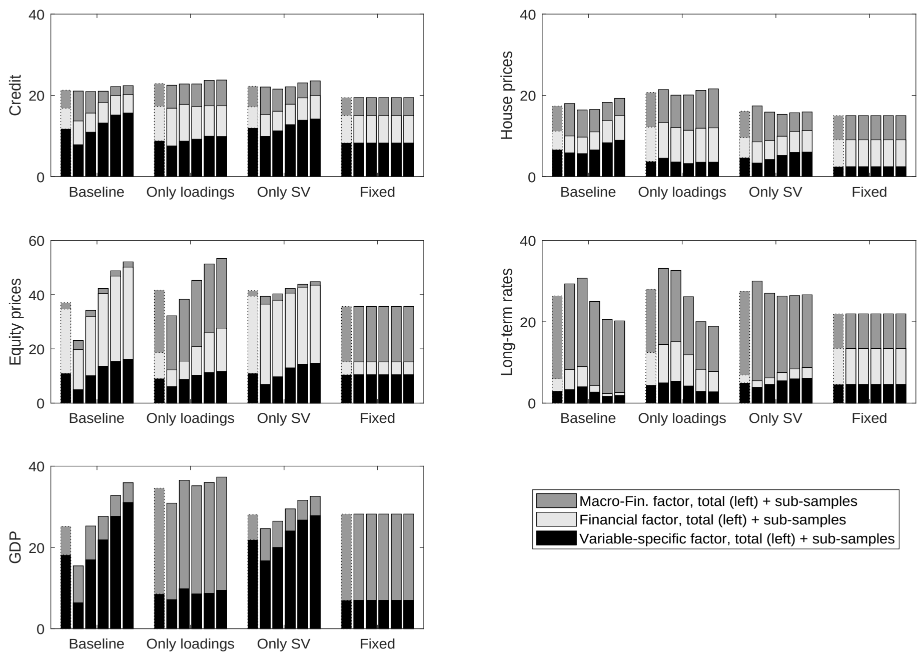

Figure A18: Explained variance shares, sensitivity to alternative factor structures.
Notes: Shares of variances explained by common factors, averaged over countries, medians over 500 retained Gibb draws. Total sample period (left bar) and sub-samples: 1880-1913 (2nd left bar), 1923-1938, 1948-1983, 1984-1998, 1999-2013 (right bar). Baseline: Model with time-variation in loadings and stochastic volatilities. Alt1: Time-variation in loadings only. Alt2: Time-variation in stochastic volatilities only. Alt3: No time-variation (fixed parameters).