KIEL
WORKING
PAPER

Global Financial Cycles since 1880

Galina Potjagailo and Maik H. Wolters

Global Financial Cycles since 1880[*]

Galina Potjagailo[†]

University of Kiel and Kiel Institute for the World Economy

Maik H. Wolters[‡]

University of Jena, Kiel Institute for the World Economy and IMFS Frankfurt

March 26, 2019

Abstract

We analyze cyclical co-movement in credit, house prices, equity prices, and long-term interest rates across 17 advanced economies. Using a time-varying multi-level dynamic factor model and more than 130 years of data, we analyze the dynamics of co-movement at different levels of aggregation and compare recent developments to earlier episodes such as the early era of financial globalization from 1880 to 1913 and the Great Depression. We find that joint global dynamics across various financial quantities and prices as well as variable-specific global co-movements are important to explain fluctuations in the data. From a historical perspective, global co-movement in financial variables is not a new phenomenon, but its importance has increased for some variables since the 1980s. For equity prices, global cycles play currently a historically unprecedented role, explaining more than half of the fluctuations in the data. Global cycles in credit and housing have become much more pronounced and longer, but their importance in explaining dynamics has only increased for some economies including the US, the UK and Nordic European countries. We also include GDP in the analysis and find an increasing role for a global business cycle.

Keywords:	financial cycles, financial crisis, global co-movement,
	dynamic factor models, time-varying parameters, macro-finance
JEL-Codes:	C32, C38, E44, F44, F65, G15, N10, N20

1   Introduction

Today's financial system is global. Banks and investment funds operate across borders and trade on international wholesale and bond markets (Kollmann et al., 2011; Kalemli-Ozcan et al., 2013). While such internationalization has brought many advantages in terms of risk diversification and an efficient flow of funds, the 2008 global financial crisis illustrated major risks. As such, credit and various financial asset classes can exhibit joint boom-bust episodes, with potentially severe repercussions on the real economy (Iacoviello, 2015; Jordà et al., 2015a,b; Menden and Prõano, 2017). In view of financial integration, fluctuations in financial quantities and prices also display a strong degree of commonality across advanced countries, such that financial fluctuations can quickly take a global dimension (Eickmeier and Hofmann, 2013).

Since the 2008 global financial crisis, a literature on the estimation of global financial co-movement has developed. 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., 2017b), 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 inconclusive empirical evidence on global financial co-movements might relate to two facts. First, existing studies focus on rather short samples of 25 to 40 years. However, financial cycles have a low frequency (Claessens et al., 2012; Borio, 2014; Rünstler and Vlekke, 2018) and boom-bust episodes are rare events, such that the consideration of a long sample period can be critical. Second, there is no consensus yet regarding which financial aggregates are relevant measures of global financial cycles. The existing studies differ in this regard: some look at risky equity returns only, or at credit and different asset prices individually, others consider composite indices of financial conditions, and yet others look at capital flows. However, joint global co-movement across financial sectors might go hand in hand with sector-specific global dynamics, while potentially evolving differently over time.

Against this background, we analyze cyclical co-movement in credit, house prices, equity prices and interest rates across 17 advanced economies based on a Bayesian multi-level dynamic factor model that allows for time variation in factor loadings and for stochastic volatility. We use over 130 years of data from the Macrohistory Database of Jordà et al. (2017) and Knoll et al. (2017). The sample covers more than 50% of world GDP over the sample period. The model decomposes the cyclical fluctuations in financial variables into global factors capturing the common dynamics across countries and variables and into idiosyncratic components specific to each time series.

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?

Two aspects of our modeling approach are central to address these questions. First, the multi-level factor structure incorporates global co-movement at different levels of aggregation and thus enhances a comprehensive picture of global financial cycles. A financial factor captures global dynamics across credit and various asset prices jointly, and is thus closely related to what is referred to as the "global financial cycle" by Rey (2015). Beyond that, we include factors that capture global dynamics specific to credit, each type of asset prices, and GDP, respectively, and we control for global linkages between financial variables and GDP. Second, the very long sample period allows to compare recurrent cycles over time, even though financial boom-bust episodes are rare events. To our knowledge, we are the first ones to incorporate gradual time-variation—with respect to the factor loadings and the variances of shocks—in the analysis of global financial cycles, instead of merely comparing sub-samples. Our sample starts with the "first era of financial globalization" prior to World War I: a period characterized by increasing shares of lending and cross-border capital flows relative to GDP (Schularick and Taylor, 2012; Reinhart et al., 2016; Knoll et al., 2017). We also compare two large-scale global financial turmoils and the subsequent recessions: the Great Depression and the Great Recession.

Regarding the first research question, we find evidence for global co-movement at different levels of aggregation, and that the estimated factors trace historic events well. There is a global financial factor capturing joint co-movement between credit, asset prices and interest rates. This factor displays both high and medium frequency fluctuations, but protracted cycles of 8 to 16 years have gained importance in recent decades. Beyond that, there is a global credit cycle and a global house price cycle that became more prolonged and ample since the 1970s reaching a length of about 15 years, as well as a global equity price cycle of a length of 3 to 5 years. Furthermore, there is a global GDP factor that shows cycles of 2 to 8 years, but also some more protracted fluctuations. We find evidence for a global macro-financial factor, but the size of macro-financial shocks declined over time.

Regarding the second question, we find that on average global co-movement explains large, but not predominant 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 that 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 pronounced differences across countries: the susceptibility to global dynamics increased in the UK, the US and in Nordic European countries, but remained constant or declined 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.

The presence of financial cycles implies new trade-offs for policy makers, in particular if such cycles have a global dimension. Central banks might need to weigh price stability against financial stability (Borio et al., 2018) and domestic monetary policy objectives against cross-country spillover effects (Bruno and Shin, 2015; Obstfeld, 2015; Cesa-Bianchi et al., 2018). At the extreme, domestic financial conditions might be driven by a global financial cycle and by monetary policy in center economies, outweighing the role of domestic fundamentals (Rey, 2015; Bruno and Shin, 2015a; Cerutti et al., 2017a). This potentially calls for internationally coordinated macroprudential policy, financial regulation and monetary policy (Rajan, 2015; Cecchetti and Tucker, 2016; Gopinath, 2017). The findings from this paper regarding the cyclical characteristics and the importance of global financial co-movement contribute to a thorough understanding of the nature of global financial fluctuations. They imply that both composite indices and individual financial sectors should be carefully monitored by policy makers. 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—as captured by the aggregate financial factor—leverage and therefore risks to financial stability might increase substantially (Jordà et al., 2015b).

There are few papers using long historical samples to analyze global co-movement of financial variables that are closely related to our analysis, but differ with respect to the financial variables considered and the method used. Jordà et al. (2019) analyse global asset-specific co-movement, but do not consider a joint global financial cycle across different financial variables. They use averaged bilateral cross-country correlations and focus in particular on the increased co-movement of equity prices since the 1990s. Bekaert and Mehl (2017) use a factor model, but their analysis is restricted to global co-movement of equity returns. Finally, Meller and Metiu (2017) study global co-movement of credit using bilateral cross-country correlations.

We confirm the results from Jordà et al. (2019) and Bekaert and Mehl (2017) of an increasing role of global dynamics for equity prices: we find that this holds for all countries in our sample and is in this sense a truly global phenomenon. Going beyond the previous findings, we observe protracted and ample common cycles for credit and house prices in recent decades. We cannot confirm that the role of global factors in explaining credit and house price fluctuations increased globally. Instead, we observe an increased importance of co-movement only for a sub-group of financially open economies including the US and the UK.[1] Hence, a country's susceptibility to global forces might depend on

---

[1]The difference in results to Jordà et al. (2019) is related to the modeling approach: when using bilateral correlations, we find results that are very similar to theirs. The dynamic factor model is advantageous in several dimensions: it provides direct estimates of common dynamics across many countries simultaneously, allows to describe the cyclical properties of co-movement both across and within financial sectors, directly

institutional characteristics and the interconnectedness of the financial system. According to our results, global linkages across financial aggregates, i.e. linkages between credit, housing and equity markets, have gained relevance in more financially open countries, and this might make them particularly reactive to global developments. Understanding cross-country heterogeneity is therefore important when thinking about the coordination of financial stabilization policies across countries and sectors.

At the same time, any study using long, historical data faces limitations regarding the data quality and its comparability over time. We take these challenges seriously by documenting our treatment of the data carefully, and by using a flexible model that we believe can partially alleviate data issues. The Bayesian estimation approach allows to exploit the long data set, while controlling for changes in the amount of noise in the data, without using unreliable data during the World War years or overly distorting results by interpolating missing data points. We use the dynamic factor model to provide a detailed description of historical patterns that is useful to understand global financial co-movement today. However, for the time being, we refrain from additionally identifying structural drivers behind historical global dynamics, given that such an exercise faces even harsher limitations related to historical data.

The remainder of the paper is organized as follows. Section 2 presents the historical data set and shows stylized 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.[2] 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.[3] 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, particularly during the 1950s

___

determines to which extent global dynamics are relevant for individual economies and explicitly models time-variation through the model parameters

[2]The authors compiled the data set based on a broad range of historical sources and publications of statistical offices and central banks. For details regarding the data sources and the construction of the data series, we refer to the online appendix published on the website.

[3]Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, UK and the US. We do not include house price data for Spain, Italy and Portugal because these series are only available from the 1970s or late 1980s onwards. However, we do run a specification including these countries. Although the higher number of missing values makes the estimation less stable, our results remain very similar.

and 1960s, we compute deviations from centered moving averages of ± 8 years.[4]

2.1 World Wars and Missing Values

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, many data points are missing and available data show strong fluctuations. These reflect the extreme economic environment of war, but also the fact that a precise collection of statistical data was most likely not a priority for many countries during the wars. At the same time, such large short-run fluctuations are very hard to grasp econometrically. 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 early era of globalization up to 1913, 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.[5]

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.[6] 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: for credit, 5 percent of total observations across countries are missing, for house prices and equity prices about 10 percent of observations are missing, and for long-term interest rates there are only a few missing data points. 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.[7] Hence, the large share of

---

[4]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.

[5]The method consists in replacing values of the log differenced variables which deviate by more than z times the interquartile range from the median of the respective series. Given that fluctuations in the historical data set are larger than in standard macroeconomic data, we set $z = 7$, whereas Stock and Watson (2005) and Eickmeier et al. (2014) used $z = 3$ and Barigozzi et al. (2014) used $z = 6$. Moreover, instead of replacing such large outliers by median values, we take a more agnostic approach and consider these observations as unknown. Our approach removes overall 27 observations, mostly around the World Wars, but keeps other rather large fluctuations such as those around 1929.

[6]The Macrohistory database includes data from 1870 onwards, but for the first decade the number of missing observations is much larger than for the subsequent period. We therefore use data from 1880 onwards to limit the number of missing values.

[7]Figures A1 to A5 in the appendix show the transformed series for all countries over the entire period,

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 sub-set of countries for the early sub-period. Also, the comparability of the data across countries is likely to be weaker in the early period.[8]

Table 1: Data summary statistics.

	Credit	House prices	Equity prices	Long-term rates
Number of countries included	17	14	17	17
Total sample, 1880 to 2013				
Total observations (130 years)	2278	1876	2278	2278
Total 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).

By taking a historical perspective, we cannot avoid making concessions regarding the quality and cross-country comparability of the data. At the same time, challenges regarding data quality also underline the need for using a flexible model that can account for missing values beyond simple interpolation as well as for variation in the volatility in the data. Within the Bayesian estimation approach, missing data points are sampled using the Kalman filter within the Gibbs sampling algorithm, and data points for the World War years are not used to update the prior. 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 variable-specific

---

also including the World War years that were not used in the estimation, and the periods with missing values. For equity prices, the majority of missing data points at the beginning of the sample refer to smaller economies. For house price and credit, data before 1900 are also missing for larger economies such as the UK (house prices) or France and Spain (credit). The figures also show that many financial series show large fluctuations and spikes during the excluded World War years.

[8]As such, the Macrohistory database mostly relies on national sources for financial data, and for many countries changing national sources over time, during the first part of the sample (Jordà et al., 2017). By contrast, for the post-war period international sources such as the International Monetary Fund or the OECD are used much more broadly. For house price series, variations in the data sources might be particularly relevant for the quality of the data during the early period, as more sources refer to urban (instead of nationwide) prices and as methodologies to measure prices differ across sources (sale prices in the market, listing prices, appraised values) (Knoll et al., 2017).

or aggregate factors) that stem not only from structural economic changes, but also from changes in data quality.

2.2 Descriptive Statistics on Historical Financial Co-Movement

Table 2 shows descriptive statistics for the time series included in the analysis, i.e. (log) differenced, detrended and standardized series. Means and standard deviations are shown for five sub-periods representing the "early era of financial globalization" (1880-1913), the inter-war period (1923-1938), the post-war period (1948-1983) and two sub-samples since the Great Moderation (1984-1998, 1999-2013). There are large changes in the level and the volatility over time calling for a flexible model allowing for stochastic volatility. The means of most variables show pronounced drops during the period covering the 1929 stock market crash and the Great Depression in the 1930s; for equity prices and GDP we also see declines during the most recent period that includes the Great Recession. Standard deviations for most series are higher during the early sub-periods, with the exception of equity prices, for which volatility is largest in the most recent sample.

Table 2: Descriptive Statistics

Mean (Standard Deviation)					
	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 $\pm$ 8 years centered moving window, and standardized.

Next, we have a look at measures of cross-country co-variation in the data based on averaged bilateral cross-country correlations.[9] Table 3 shows these measures with respect to each variable separately, the four financial variables jointly (column "Finance"), and all five variables jointly, i.e. financial variables and GDP (column "All"). This gives us a first indication of the size of cross-country co-movements for each variable and across variables, and we can check for potential differences over time based on simple sub-sample comparisons. In the computation of these measures, we have to deal with missing values outside of the Gibbs sampler, and we extra- and interpolate missing values linearly. Results are similar when we exclude the countries with missing data.

Variable-specific correlations increase strongly over time, but those for interest rates and equity prices also show a "swoosh" shape, being highest in the inter-war sub-sample

---

[9]We have also computed descriptive statistics based on static principal components that are available upon request.

and in the most recent sub-sample. Correlation levels between all four financial variables and between the four financial variables and GDP are overall rather small; they increase slightly over time until the end of the 1990s and roughly double during the most recent sub-sample. This provides a first indication that the role of a global financial cycle and a macro-financial cycle might have increased in recent years.

Table 3: 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.

However, results for these simple measures might draw an incomplete picture. Bilateral correlation measures do not account for co-movement across many countries simultaneously. In addition, the correlations from each variable are not conditioned on each other and thus might capture spurious co-movement. Indeed, global co-movement jointly across variables appears much smaller than variable-specific co-movement according to these measures. Further, the sub-sample results need to be taken with much caution given that they are based on short time periods and might thus be estimated imprecisely and might overstate the degree of co-movement. Indeed, the measures show a rather low co-movement over the total period compared to the sub-sample results. Also extra- and interpolation of missing values might bias the results. The dynamic factor model will address these issues via the multi-level factor structure and by exploiting the full sample period while sampling missing values and while allowing for time-variation through the parameters.

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.[10] 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).[11]

The log volatilities of the K factors and of the n idiosyncratic components follow drift-less 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 $\Omega_\eta = diag(\sigma_{\eta 1}^2, ..., \sigma_{\eta K}^2, \sigma_{\eta K+1}^2, ..., \sigma_{\eta K+n}^2)$. The variances $\sigma_{\eta 1}^2, ..., \sigma_{\eta K}^2$ correspond to the volatilities of factors, and $\sigma_{\eta K+1}^2, ..., \sigma_{\eta K+n}^2$ 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 $\Omega_\epsilon = diag(\sigma_{\epsilon 1}^2, ..., \sigma_{\epsilon(n \times K)}^2)$. 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

---

[10]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. Ha et al. (2017) extend a linear DFM for dependencies between selected macro and financial factors in order to model macro-financial spillovers, but without allowing for a common macro-financial factor. Within the time-varying framework, we leave such an analysis for future research and focus on the contemporaneous co-movements via factors.

[11]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).

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 hierarchical factor structure, to load positively on that factor.[12]

3.1 Multi-Level Hierarchical 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 hierarchical 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.[13]

---

[12]Results stay roughly similar when instead, for each factor, the loadings of one of the US, or alternatively, of the UK variables are restricted to be positive.

[13]We do not include regional factors, but only allow for cross-country heterogeneity via the factor loadings. It is difficult to a priori define country groups over the long sample period. 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 some of the euro area economies might have been stronger with the UK, which in turn had close links to Australia and Canada via the British Empire. At the same time, we expect regional factors to be a priori less relevant given that we consider 17 advanced economies with rather similar characteristics.

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

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

where Y_t^{gdp} are the real 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 depend on the macro-financial factor f_t^{MF}. Further, zero restrictions are imposed on the loadings matrix 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).

3.2 Priors

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

$$\sigma_{\epsilon_i}^2 \sim IG(\nu_\epsilon, s_\epsilon^2),$$

$$\sigma_{\eta_j}^2 \sim IG(\nu_\eta, s_\eta^2),$$

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 want 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 estimated factors. At the same time, we want to incorporate the belief that, over the long period under consideration, sizable smooth changes in the susceptibility of

11

individual time series to global shocks may well have occurred due to structural developments specific to that variable or country. We therefore choose the priors such that variation in the loadings is favored somewhat 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.[14] In particular, we set $s_\epsilon^2 = 0.1$ for the scale of the loadings and $s_\eta^2 = 0.025$ 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 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.[15] In the second block, we sample the factors conditionally on the hierarchical 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.[16]

---

[14]Del Negro and Otrok (2008) follow a similar approach in their analysis of global business cycle comovements between 1970 and 2005, in order to achieve smooth variation not only in the stochastic volatilities, but also in the loadings.

[15]Prior to Gibbs sampling, 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).

[16]In order to estimate the autoregressive coefficients in equation (3) via Maximum Likelihood, we need

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.[17]

4 Results

4.1 Global Factors

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. There is significant global co-movement of a cyclical nature jointly across variables, i.e. between GDP and financial variables (the macro-financial factor) as well as between credit and various asset prices (the financial factor), throughout the sample period. 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.

Conditionally on these two aggregate factors, there is substantial variable-specific financial co-movement in credit, house prices and equity prices. Global 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. 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 in section 4.3, 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.

Overall, there is significant global co-movement at different levels of aggregation. The aggregate factors have a smaller amplitude compared to the variable-specific factors. The

---

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.

[17]Figure A6 in the appendix shows the recursive means and recursive variances of the Gibbs sampler draws for selected state variables.
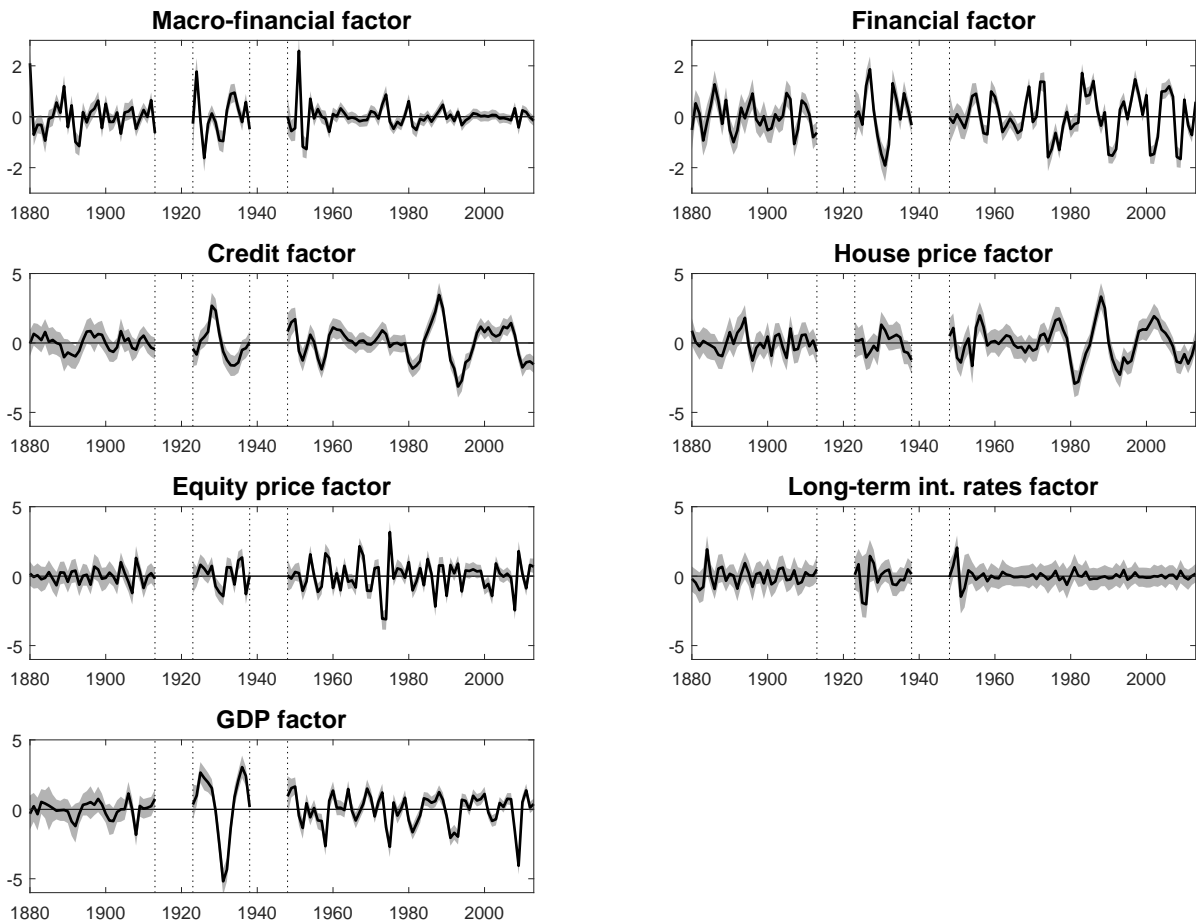
Figure 1: Global Factors

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).

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 4.2.

4.1.1 Factor Loadings

Figure 2 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. With some exceptions that we mention below, most loadings do not show large changes over time.[18]

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 all long-term interest rates load

---

[18]Additional figures showing the evolution of factor loadings over time are shown in the appendix (see also section 4.3 for a discussion.
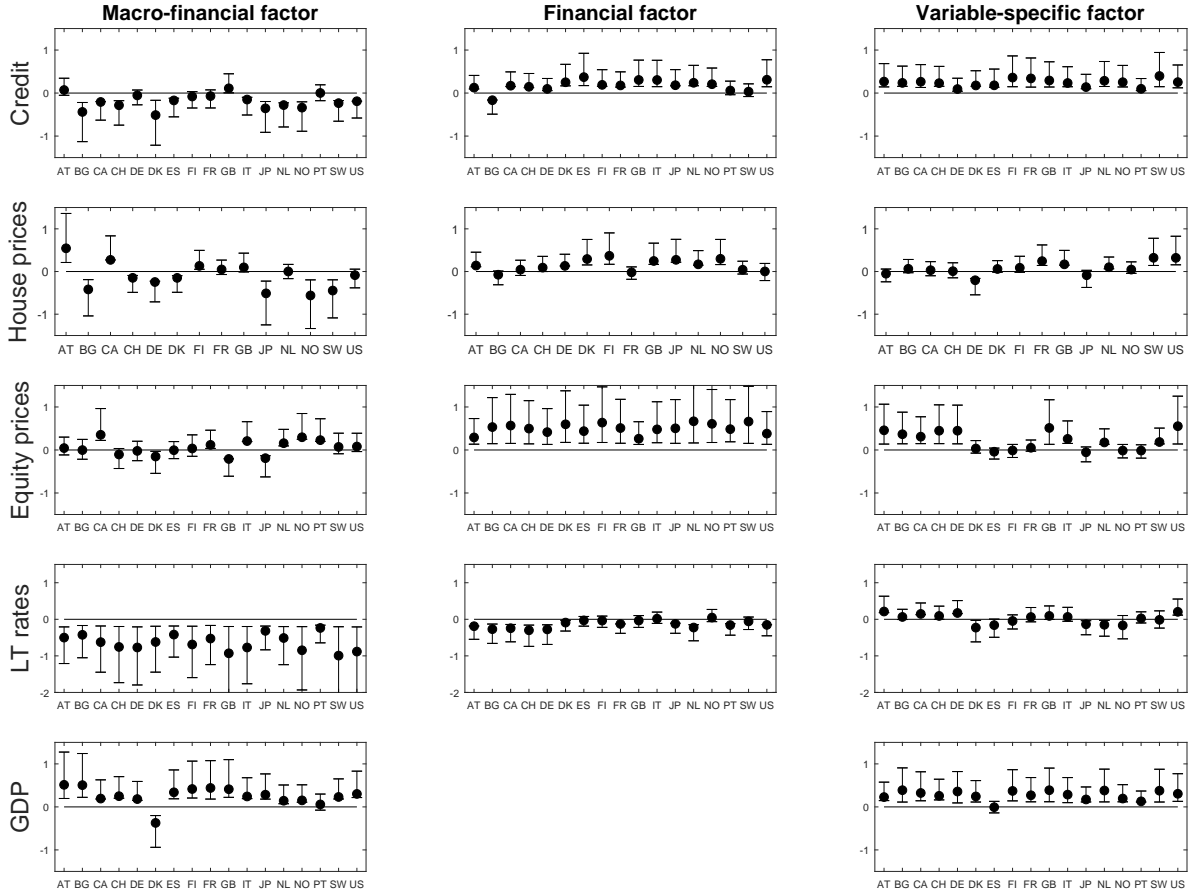
Figure 2: Loadings by variables and countries, average over total sample period.
Notes: Medians over 500 retained Gibbs draws (circle markers) and 68 percent credible sets (whiskers).
Loadings are averaged over time. GDP series do not load on the financial factor via the multi-level factor
structure.

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 synchronized contemporaneous co-movements between GDP and these series, but rather macro-financial linkages for selected 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. This role of the financial factor is particularly strong for equity prices and increases substantially over time in most countries (Figure A10). 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.

15

Turning to the variable-specific factors, all credit series load significantly positively on the credit factor, so that the credit factor in fact captures synchronized global co-movement. Only some of the house price series load significantly positively on the global house price factor, while there is no link for others 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 towards positive co-movement. 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 A11).[19] Next, more than half of the equity returns 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; most of the global dynamics in their equity prices seem to be fully captured by the financial factor.[20] 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 Global Factors and Historical Events

In how far do the estimated factors capture historical episodes of recessions and financial fluctuations? We discuss this question for different sub-periods covered by our data, and we compare the dynamics of global factors during the Great Depression following the 1929 stock market crash and the great Recession following the 2008 financial crisis.

Dynamics during the "early era of financial globalization" between 1880 and 1913 are mostly reflected by fluctuations in the two aggregate factors. The macro-financial factor shows a prolonged bust during the Depression 1882-85 and around the Panic of 1893 and shorter and smaller busts during the Panics of 1901 and 1907. The financial factor shows a boom starting in the mid-1880s after the Depression of the early 1880s, followed by a bust in 1893, as well as boom-busts around the 1907 and 1910/11 panics. The variable-specific global factors are mostly insignificant during the early era, although the credit, house price and GDP factors show marginally significant declines around 1893, and the equity price factor shows significant short-lived fluctuations around 1907 and 1911.

Figure 3 shows the estimated factors again for the periods around the Great Depression (t=0 at 1930, dashed lined) and the Great Recession (t=0 at 2008, solid lines). The two episodes appear overall not too different in terms of the fluctuations in the global factors, which underlines the recurrent nature of global financial boom-bust episodes and associated

---

[19]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.

[20]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.

recessions over the historical time period. In particular, the fluctuations in global credit are very similar across the two episodes. Also the global financial factor behaves quite similarly, but it displays a more prolonged slump during the Great Depression, opposed to a double-dip during the Great Recession associated with the euro area sovereign debt crisis. Greater differences occur for global asset prices. The slump in equity prices is more persistent during the Great Depression reflecting the persistent effects of the 1929 stock market crash. 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 fluctuations of 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. This result reflects the larger and more protracted downturn during the Great Depression caused by tight monetary policy due to the gold standard, while the aggressive use of monetary and fiscal policy measures, together with the prevailing flexible exchange rate frameworks, alleviated the drop in global GDP in the recent episode compared to the Great Depression (see, e.g., Almunia et al., 2010).
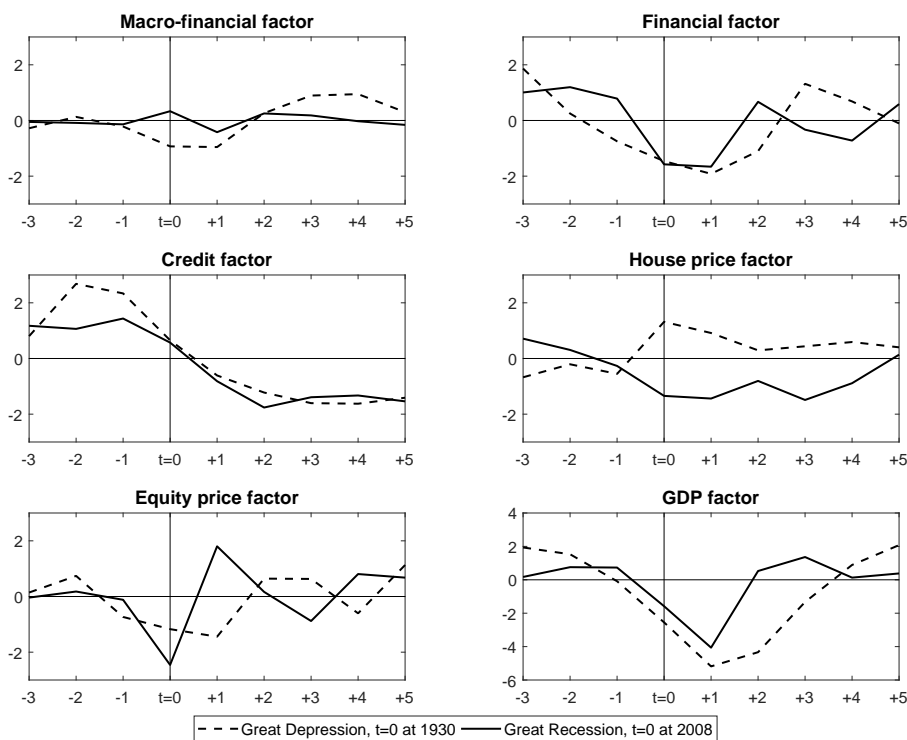

Figure 3: Great Depression vs. Great Recession, Estimated Global Factors.

Turning to the post-war period, we observe rather short-lived fluctuations in most financial factors during the 1950s and a recession in the global GDP cycle ("Eisenhower Recession" 1958). The Bretton-Woods era characterized by global capital controls is reflected in the fact that the global credit and house price factors, as well as the macro-financial

factor, stay mostly flat during the 1960s until the beginning of the 1970s; global GDP also shows relatively small fluctuations during that period. The global equity price cycle shows a very strong drop during the stock market crash of 1973-74 which is also associated with a prolonged bust in the aggregate financial cycle during the 1970s and a recession in global GDP.

For the period since the 1980s, we observe lengthy and ample boom-bust episodes which are most pronounced for the credit and the house price factor. After a trough during the early 1980s recession, captured by the global GDP factor, the credit and the housing factor and to a smaller extent the global financial factor reflect the housing boom in 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 during the 1990s, the housing boom that preceded the global financial crisis, as well as the subsequent bust 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 reflect truly global developments that are much different from dynamics observed for the previous 100 years. The global equity price factor reflects the stock market turbulences around the end of the 1980s and beginning of the 1990s, the burst of the dot-com bubble and the dynamics around the 2008 global financial crisis. The GDP factor captures all the major cycles since the 1980s including the early 1980s recession, the early 1990s recession, and the 2001 and the 2008-2009 recessions.

Overall, the estimated global factors trace historic events well. During some periods, major events are captured predominantly by global joint fluctuations across variables, but during others variable-specific co-movement is important as well. The pronounced global credit and house price cycles since the 1980s stand out in this respect. Hence, for policy makers it is important to monitor both, global movements in composite indices as well as in individual financial sectors.

4.2 Cyclical Properties of Global Factors

The global factors presented above appear to exhibit different amplitudes and fluctuations of different and potentially time-varying lengths. In order to assess the cyclical properties of the factors in greater detail we use two approaches: we identify cycle lengths and amplitudes via the Bry-Boschan cycle dating algorithm as in Harding and Pagan (2002), and we consider the estimated factors within the frequency domain via spectral density analysis (see Verona (2016) and Strohsal et al. (2019) for related analyses for domestic financial cycles). We do this for the total sample period as well as for various sub-samples: the early era 1880-1913, the early era and the inter-war period 1880-1938 (excluding the years 1914

18

to 1923), the post-war period until the end of Bretton-Woods 1948-1972, and two recent sub-samples, starting in 1973 until 2013 ("post-Bretton-Woods") and starting in 1984 until 2013 ("Great Moderation + Global Financial Crisis").

Table 4 shows the results from the Bry-Boschan dating algorithm. After identifying peaks and the number of cycles, i.e. periods between subsequent peaks, we show the average cycle length for each factor as well as the maximum and average amplitude in terms of the distance between the maximum peak and lowest trough and the average peak and trough, respectively.[21]

Table 4: 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 Mode-ration/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	**1**	1	1	1	0	0
Financial	**2**	1	1	2	3	3
Credit	**4**	2	4	3	7	11
House prices	**3**	1	1	2	10	10
Equity prices	**1**	1	1	2	2	1
Interest rates	**1**	1	1	1	0	0
GDP	**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.

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. The

---

[21]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, but the lengths of the GDP factor and of the aggregated factors increase somewhat.

amplitudes of GDP, the credit and house price factors are higher compared to the other variables. When looking at the maximum amplitude, the GDP factor shows the largest amplitude driven by the very large swing during the Great Depression. The credit and the house price factors has just a slightly smaller amplitude during the credit and house price cycle of the 1980s.

There is substantial variation over time for some of the factors. Cycles were particularly short and of low amplitude in the Bretton-Woods period reflecting the fact that capital controls limited financial fluctuations during this period. The cycle length and amplitude of the credit and house price factors increased substantially after the end of the Bretton-Woods era, with the longest and most pronounced cycles of 15 years length occurring in the most recent subsample starting in 1984. This reflects the pronounced parallel boom-bust cycles in credit and housing since the 1980s described above. The GDP factor exhibits long cycles of about 12 years before WW2 reflecting in particular the long cycle during the Great Depression. Fluctuations after WW2 start with short-lived cycles, but since the 1970s the global business cycle length has increased substantially up to 10 years. By contrast, for equity prices and long-term interest rate there is little change in the cyclical properties over time.

Figure 4 shows the spectral densities of the estimated factors for cycle lengths between 2 and 32 years over the total sample period (black solid lines) and over sub-samples. They provide a more complete picture of the presence of cycles of different frequencies in the factors, as all cycle lengths relevant for a factor can be detected instead of only considering average lengths. Peaks in the spectral densities indicate recurrent cyclical fluctuations of the respective length. The results reveal that the aggregate 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. In particular, the spectral density of the financial factor shows peaks both at cycle lengths of above 8 to 16 years as well as at lengths of 3 to 6 years. By contrast, the equity price factor and long-term interest rate factor show fluctuations predominantly at short cycle lengths of 3 to 5 years, whereas the credit and house price factor cover spectra corresponding to cycles of above 8 up to 20 years. Finally, the global GDP cycle shows a large share of fluctuations at frequencies corresponding to 4 to 6 years and between 8 and 20 years.

Overall, the results of the spectral density analysis go in the same direction as the ones of the algorithm-based analysis. In the early part of our sample both the aggregate financial cycle and the variable-specific cycles show somewhat less regular cycles with cycle lengths and amplitudes similar or even smaller compared to the global business cycle. However, financial cycles became more prolonged and ample since the 1970s. This holds in particular for global credit and house prices. We find that these variable-specific cycles show a longer length and higher amplitude compared to the aggregate factors since the 1970s. Thus, controlling for variable-specific cycles is important to capture substantial global financial
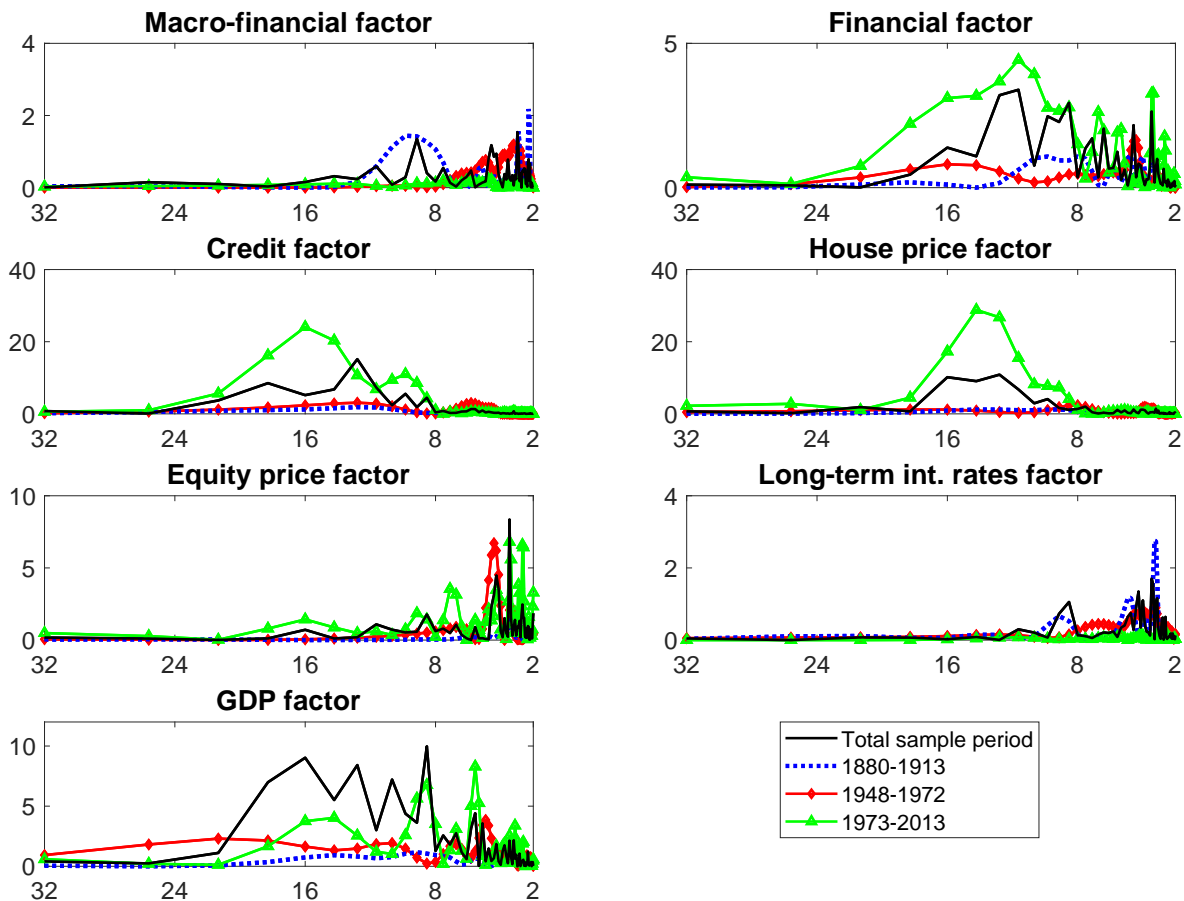
Figure 4: Spectral densities of estimated factors.
Notes: The x-axis measures the length of cycles from 2 years to 32 years. Spectral densities are based on detrended, differenced series and are computed over the total period (black solid lines) and over the sub-samples 1880-1913 (early era, blue dotted 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.

fluctuations at different frequencies. Our findings confirm the results from earlier papers that cover recent sample periods and that observe a financial cycle length of 15 to 20 years, 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 dynamics of global financial co-movement is in line with Filardo et al. (2018), who, based on a long sample period, find that the US credit cycle became more protracted during the post-War period.

4.3 Importance of Global Co-Movement

Having provided a detailed picture of the characteristics of historical global financial cycles, we now turn to the question of how relevant these common shocks are for explaining fluctuations in the individual time series relative to idiosyncratic fluctuations. For this purpose, 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. In order to summarize the results, we present variance decompositions for each variable, averaged over the total sample period as well as over five sub-samples. Table 5 distinguishes explained variance shares by factor types and shows credibility sets, summarizing the results across countries. In addition, 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).[22]

Table 5: 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.

In the upper part of Table 5 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

___
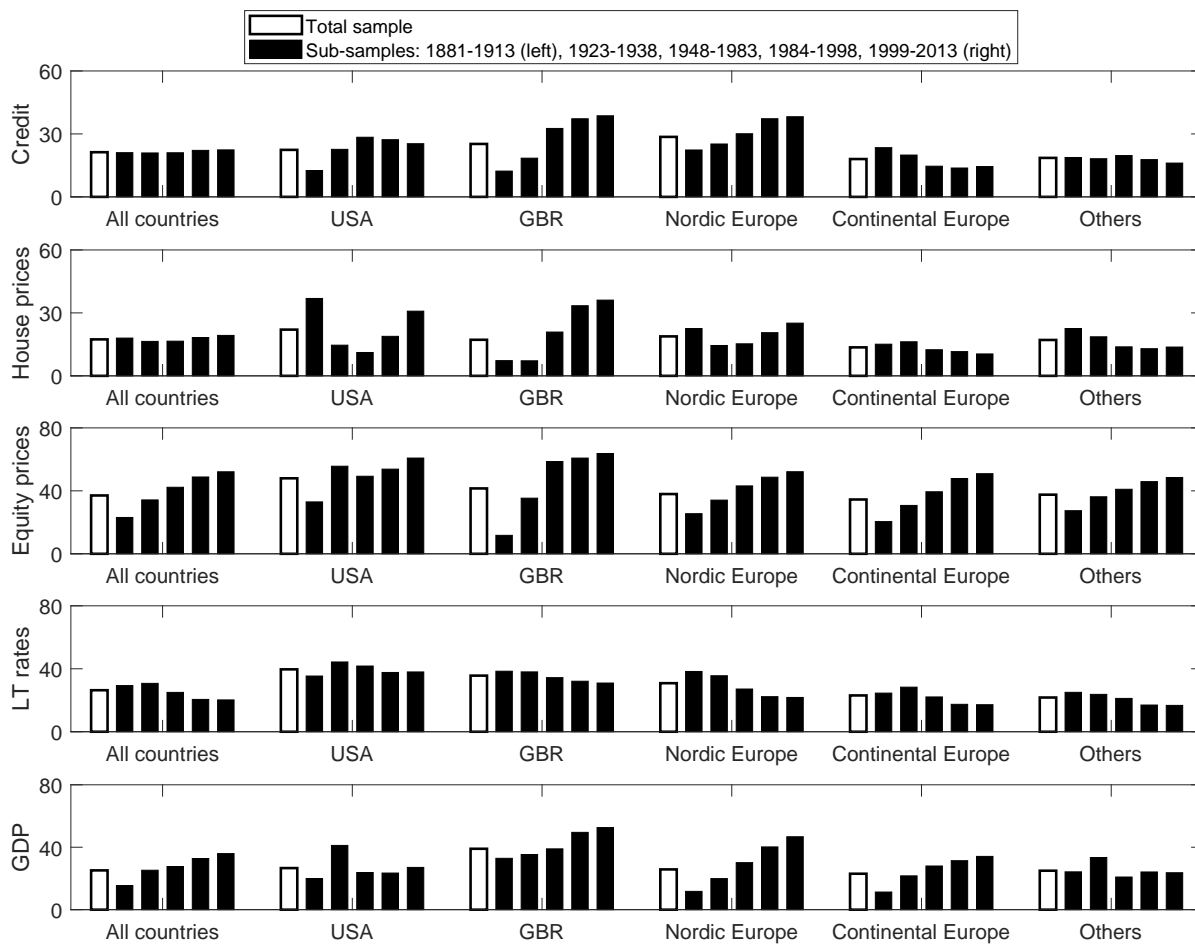[22]Figure A7 in the appendix shows more detailed results for each country.

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.

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.

In how far did the role of global factors change over time? The lower panel of Table 5 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 roles both of the aggregate financial factor and the equity price factor, explaining 34 percent and 16 percent of equity price fluctuations in the recent period, respectively. Strikingly,

23

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. For credit, the role of the global credit factor increased while the variance shares explained by the aggregate factors declined, leading to almost no change in sum. For house prices, a weak "swoosh" shape is observed, with the macro-financial factor becoming less important over time, but the financial factor and the house price factor becoming more important over the two recent sub-samples. For long-term interest rates, we observe a slight decrease in the role of global factors that is also observed for most countries. However, for credit and house prices, the aggregate results mask important heterogeneity across countries regarding the time variation in the role of global co-movement. 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 Japan, the role of global factors stays stable or even declines over time.[23]

Finally, 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. The role of GDP-specific global co-movement increased fivefold by the end of the sample period compared to the early era of financial globalization. Back then, the role of the macro-financial factor was more dominant, but only 15 percent of fluctuations in total were due to global dynamics. The 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 which we report in Figures A8 to A12 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: the loadings to the respective variable-specific factor and to the financial factor increase over time only for some economies (mainly US, UK and some Northern European

---

[23]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.

countries), but stay rather constant or even decrease in others. Finally, according to the model, the decline in the importance of the macro-financial factor for most series stems from a strong decline in the size of macro-financial shocks. This reflects that the macro-financial factor mainly captures the high volatility period during the early era of financial globalization and the Great Depression.[24]

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 might make equity return dynamics a truly global phenomenon. On the other hand, regarding credit aggregates and house prices, a country's susceptibility to global forces might depend to a larger degree on institutional characteristics and the interconnectedness of the domestic banking sector. The observed country differences suggest that financial aggregates in more financially open economies are more reactive to global developments.[25,26] In addition, global linkages across financial aggregates, i.e. linkages between credit, housing and equity markets, seem to have gained relevance for more financially open economies in particular, as indicated by increased loadings to the financial factor. This might imply an increased presence of "leveraged bubbles" across financial sectors on a cross-country scale potentially related to financial deregulation (Jordà et al., 2015b; Iacoviello, 2015; Bengui and Phan, 2018). Accordingly, understanding cross-country heterogeneity can be essential when thinking about the coordination of financial stabilization policies across countries and sectors.

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.[27]

---

[24]The decline in volatility in the factor with the highest level of aggregation might also reflect changes in the quality of the data. The decline is most steep after World War II, but slows down towards the end of the sample period.

[25]These important cross-country differences were concealed in earlier studies that relied on averaged bilateral cross-country correlations rather than using a dynamic factor model.

[26]La Porta et al. (1997) show that the US and the UK are financially highly open economies and Honkapohja (2009) and Jonung (2009) document a large wave of financial deregulation in Northern European countries starting in the 1980s.

[27]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 onwards, 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.

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 A13 and A14 in the appendix.

The one-level model with variable-specific cycles provides a credit and house price factor that is robust 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 one 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, with find less variation over time for the other financial aggregates compared to equity prices. Models that additionally include bilateral 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 A15 and A16 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 analyzed cyclical co-movement in credit, house prices, equity prices and long-term interest rates across 17 advanced economies based on a multi-level, 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 are important to explain global fluctuations. Second, global co-movement explains a significant, but not a predominant share of dynamics of financial aggregates on average across countries. For equity prices the picture is special: global cycles explain more than half of the fluctuations and their role continuously increased over the historical time span that we consider. For the other financial aggregates, the role of global cycles is overall lower and not so new from a historical perspective. In case of credit and house prices 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 bare 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. At the same time, the complex behavior of global financial cycles, with co-movement occurring potentially 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 determine the relevance of financial stabilization policies and 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. The analysis also opens avenues for future research. The output from the dynamic factor model, i.e. the estimated factors and the time-varying variance decompositions, can be used in a next step to investigate the historical role of country-characteristics for the susceptibility to global financial dynamics, and to look at the drivers of global cyclical fluctuations such as monetary policy or risk perceptions in center economies. Also an explicit modeling of the role of cross-country capital flows for global co-movement in financial variables deserves attention from a historical perspective. Addressing such questions requires overcoming various challenges related to data availability and identification in a historical context with annual data and potential instability over time, 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.

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.

Barigozzi, M., A. M. Conti, and M. Luciani (2014). Do Euro area countries respond asymmetrically to the common monetary policy? *Oxford Bulletin of Economics and Statistics 76*(5), 693–714.

Bekaert, G. and A. Mehl (2017). On the global financial market integration "swoosh" and the trilemma. NBER Working Paper 23124.

Bengui, J. and T. Phan (2018). Asset pledgeability and endogenously leveraged bubbles. *Journal of Economic Theory 177*, 280–314.

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

Borio, C. E., P. Disyatat, M. Juselius, and P. Rungcharoenkitkul (2018). Monetary policy in the grip of a pincer movement. BIS Working Papers No. 706.

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.

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 11042.

Cerutti, E., S. Claessens, and L. Ratnovski (2017). Global liquidity and cross-border bank flows. *Economic Policy 32*(89), 81–125.

Cerutti, E., S. Claessens, and A. K. Rose (2017). How important is the global financial cycle? Evidence from capital flows. NBER Working Paper 23699.

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

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., L. Gambacorta, and B. Hofmann (2014). Understanding global liquidity. *European Economic Review 68*, 1–18.

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.

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 18362.

Honkapohja, S. (2009). The 1990s financial crises in Nordic countries. Bank of Finland Research Discussion Papers 5.

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

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.

Jonung, L. (2009). Lessons from the Nordic financial crisis. In J. K. Jonung, Lars and P. Vartia (Eds.), *The Great Financial Crisis in Finland and Sweden. The Nordic Experience of Financial Liberalization*, Chapter 10, pp. 301–324. Edward Elgar Publishing.

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.

La Porta, R., F. Lopez-De-Silanes, A. Shleifer, and R. W. Vishny (1997). Legal determinants of external finance. *Journal of Finance 52*(3), 1131–1150.

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 21722.

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

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. (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.

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).

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

Appendix
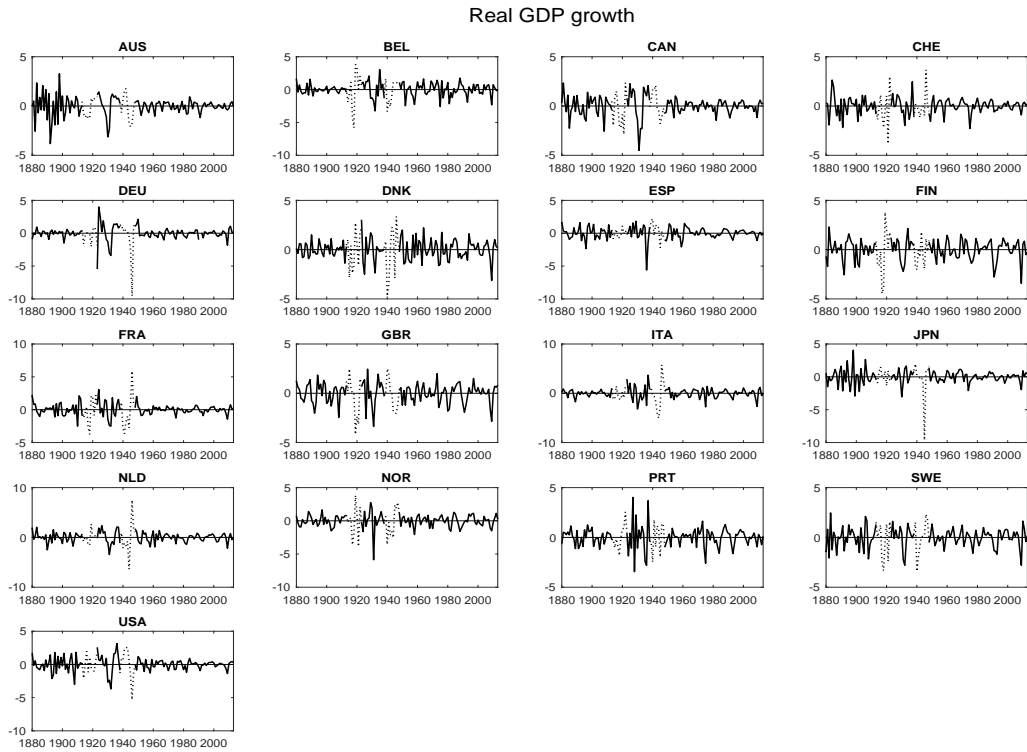
Figure A1: Log real GDP growth.
Notes: Log differenced time series. Growth rates were detrended via a centered moving average of $\pm$ 8 years and then standardized. Dotted parts show years around World Wars (1914 to 1922, 1939 to 1947) that were not used in the estimation.
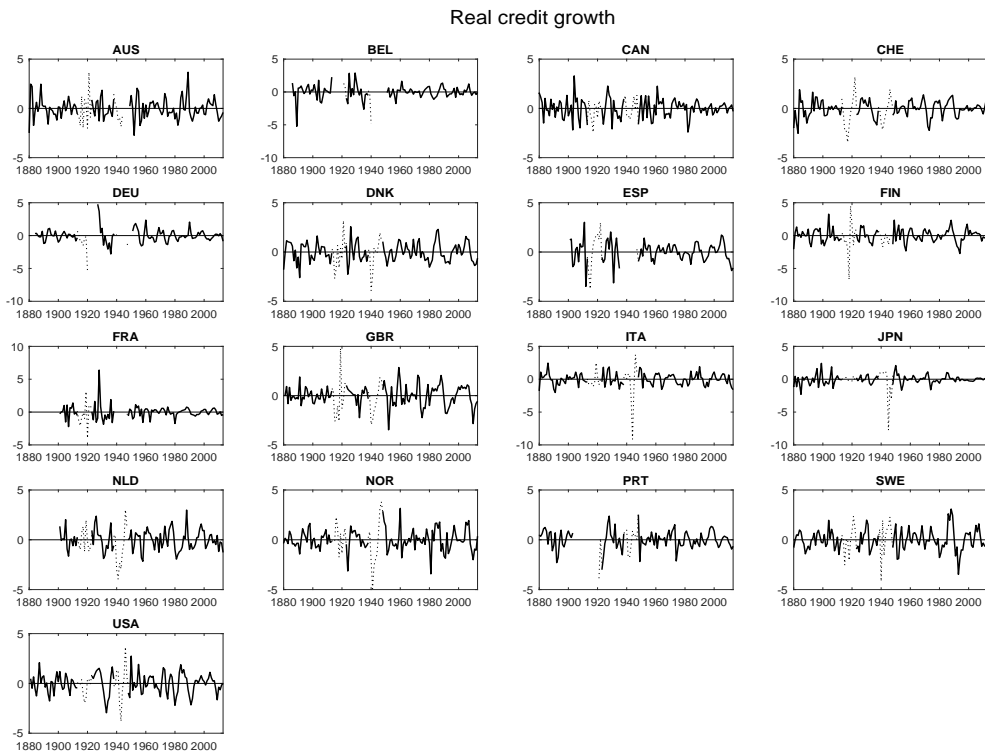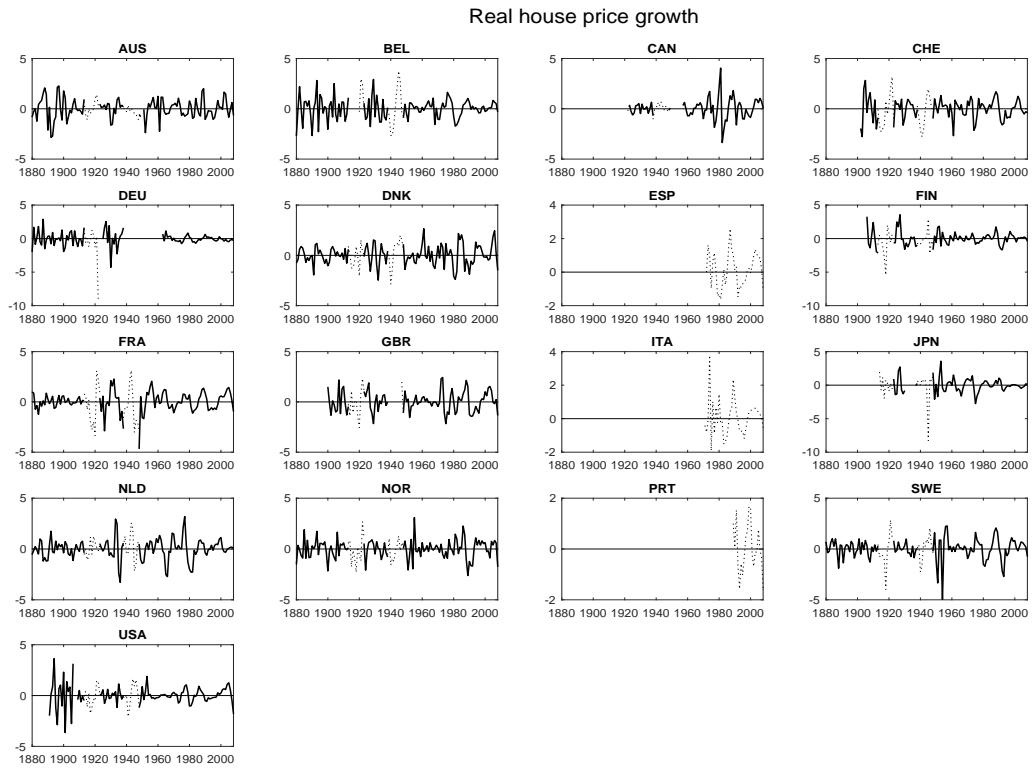

Figure A2: Log real credit growth.
Notes: Log differenced time series. Growth rates were detrended via a centered moving average of $\pm$ 8 years and then standardized. Dotted parts show years around World Wars (1914 to 1922, 1939 to 1947) that were not used in the estimation. Empty parts indicate missing values.

Real house price growth

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.

Real equity returns
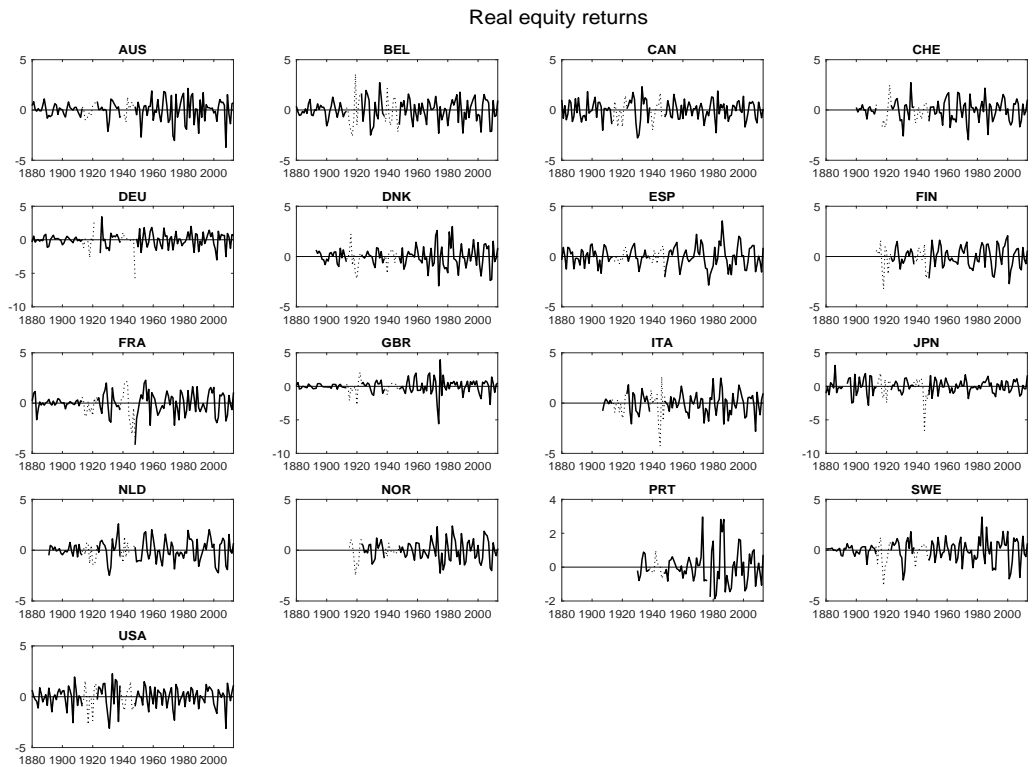
Figure A4: Log real equity returns.
Notes: Growth rates were detrended via a centered moving average of ± 8 years and then standardized. Also see notes of Fig.A2.
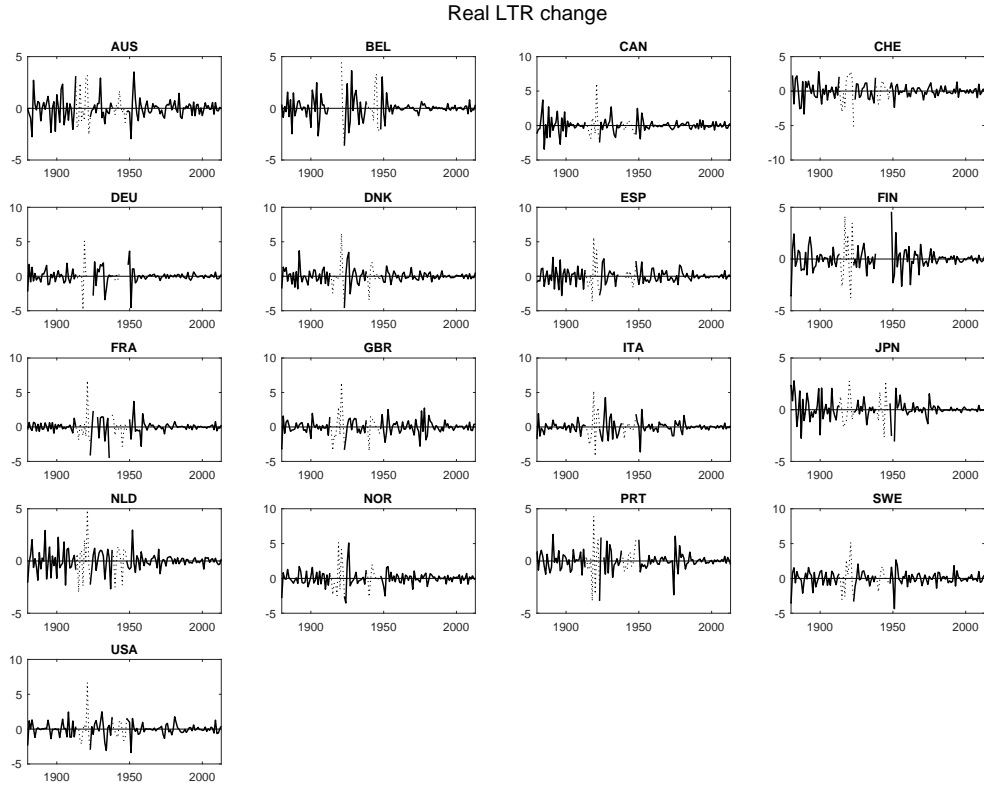
Figure A5: Differenced real long term interest rates.
Notes: Differenced time series were detrended via a centered moving average of $\pm$ 8 years and then standardized. Also see notes of Fig.A2.
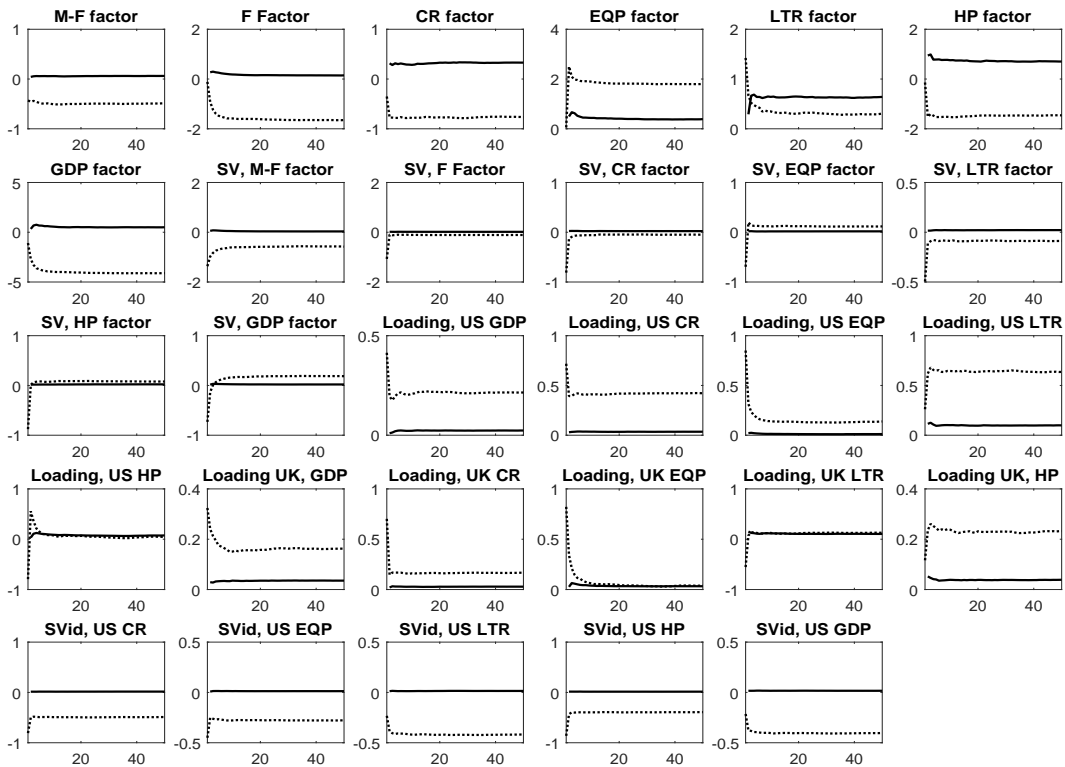
Figure A6: Recursive means and variances of Gibbs sampler draws, selected state variables.
Notes: Dotted lines show recursive means and solid lines show recursive variances of draws, calculated after every 400th draw (i.e. every 8th draw is retained and every 50th time recursive moments are calculated), for the respective state variables at t=2010.

36
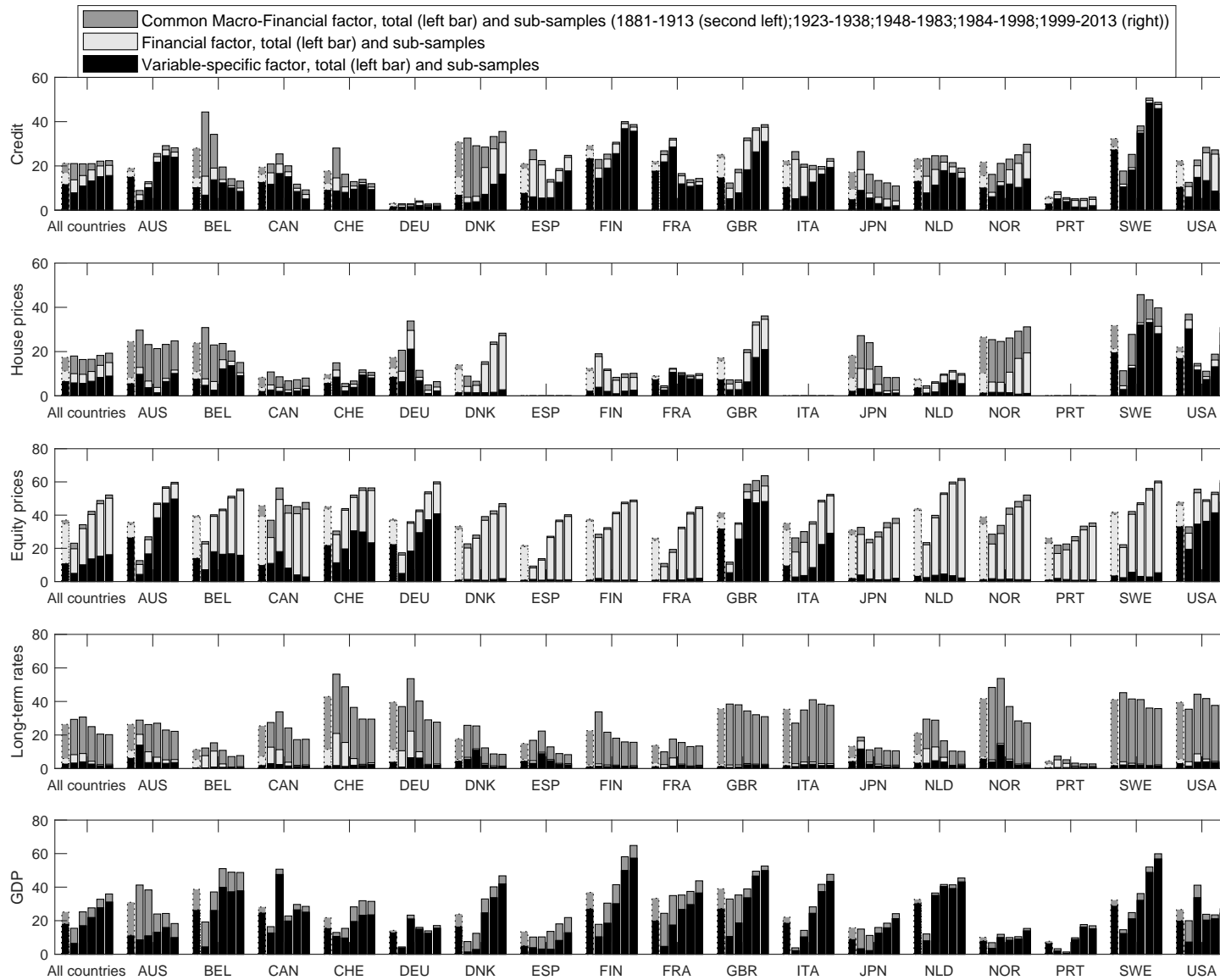
Figure A7: Total variance explained by global factors, by countries and factor type.

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).
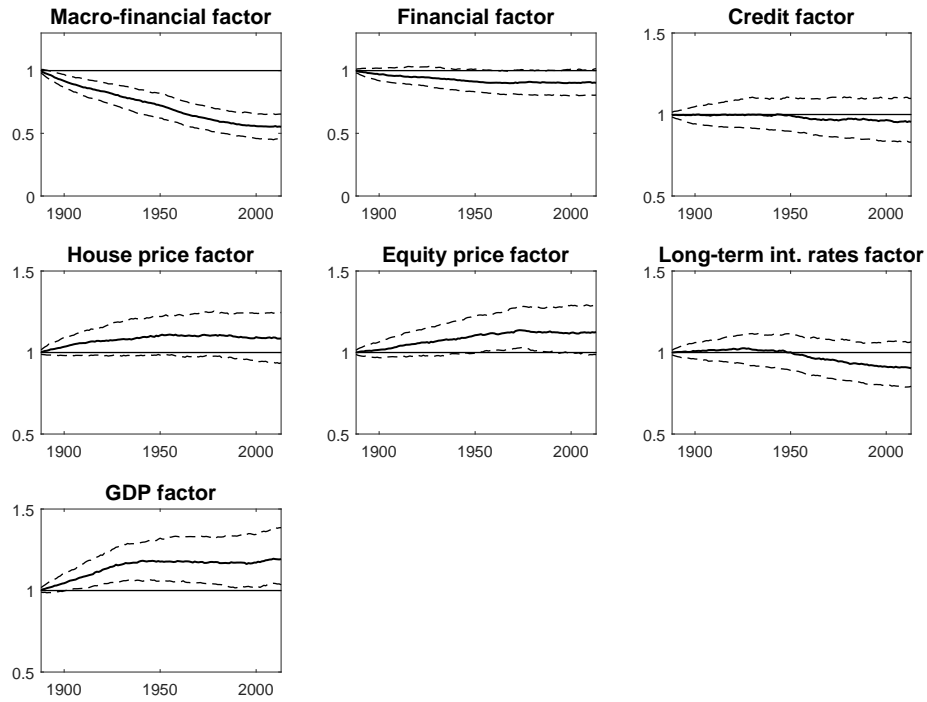
Figure A8: Stochastic volatilities of global factors.
Notes: Solid lines show the posterior median, dashed lines show the 68 percent credible sets.
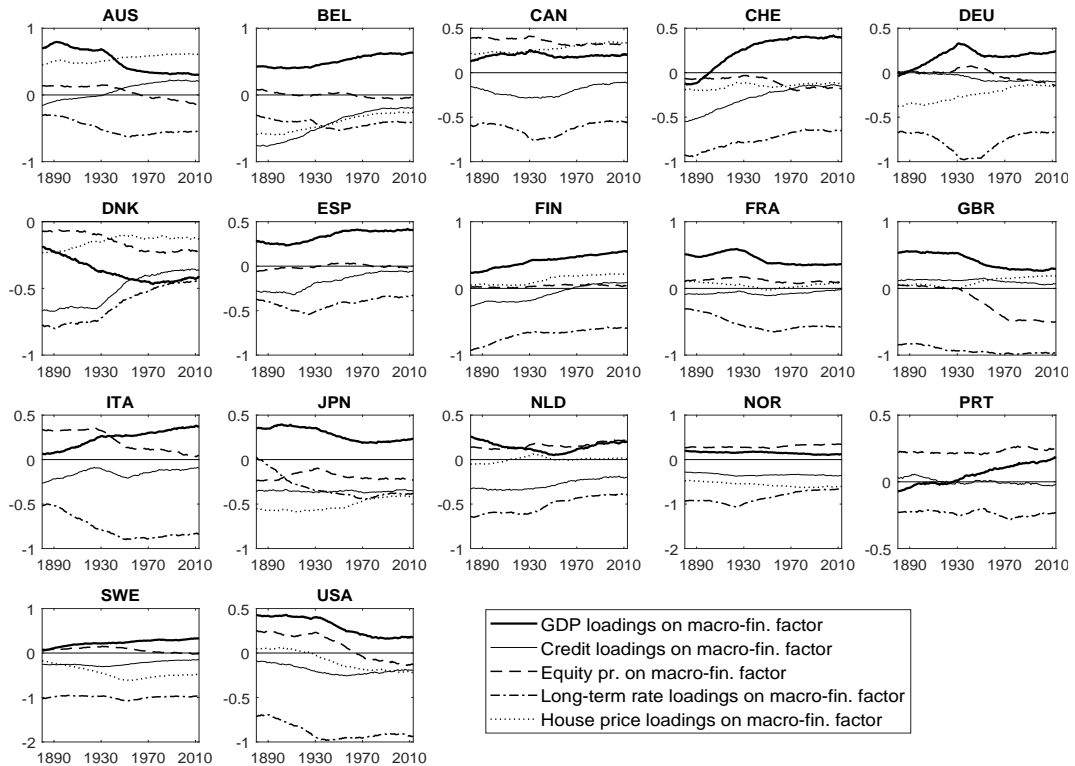
Figure A9: Factor loadings on macro-financial factor.
Notes: Estimated with the hierarchical TVP DFM. Credibility sets not presented for readability.
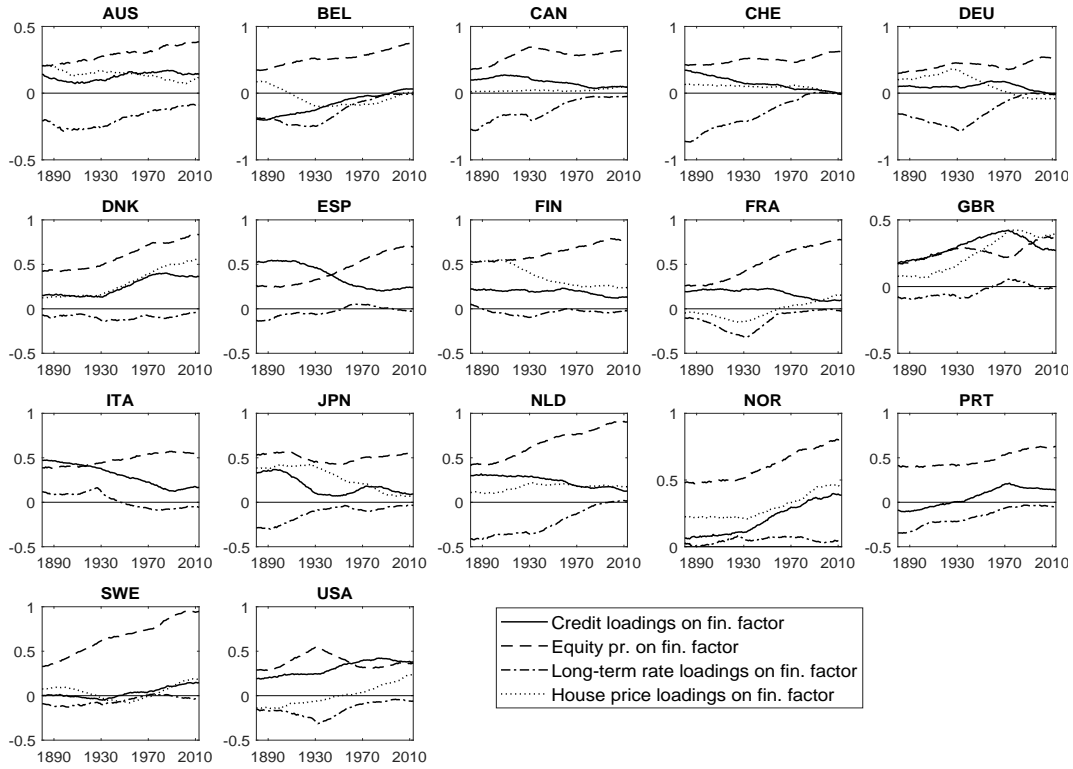
Figure A10: Factor loadings on financial factor.
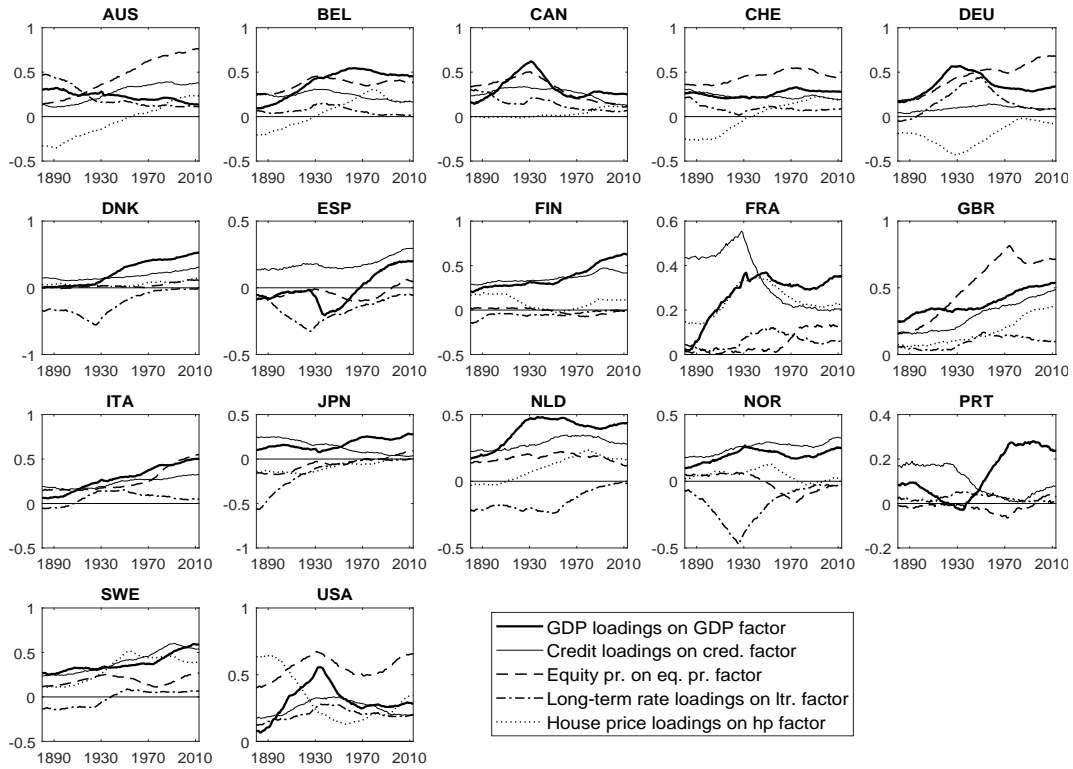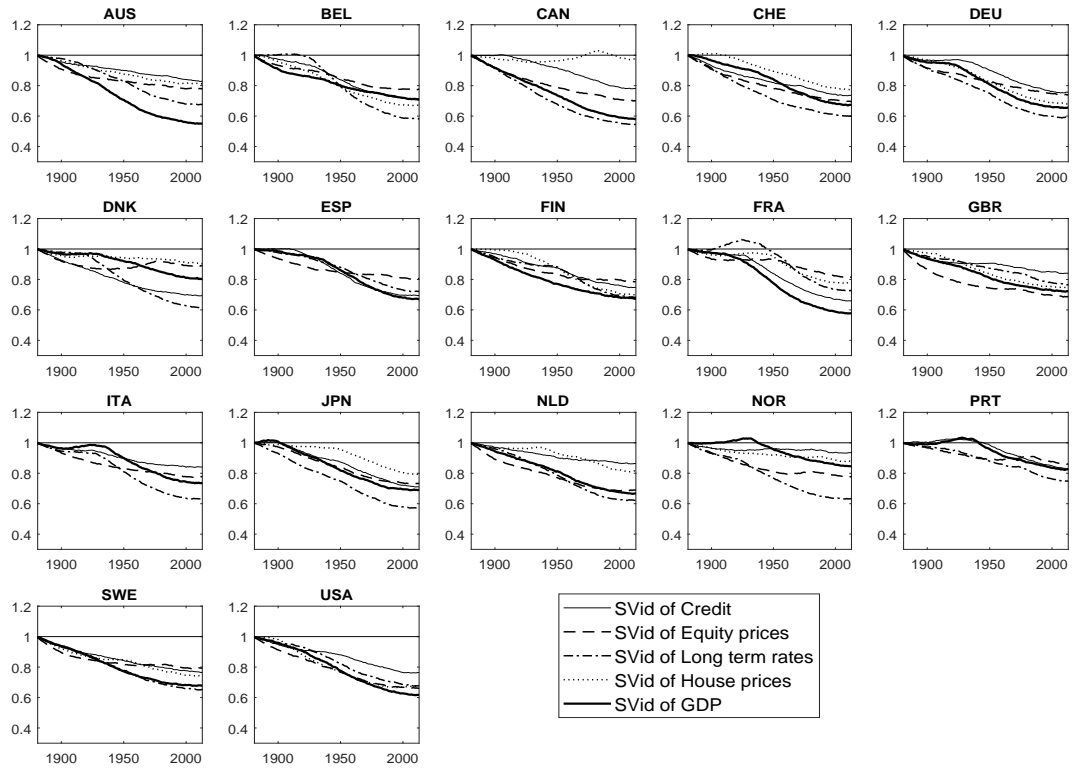Notes: Estimated with the hierarchical TVP DFM. Credibility sets not presented for readability.

Figure A11: Factor loadings on variable-specific factors.
Notes: Estimated with the hierarchical TVP DFM. Credibility sets not presented for readability.

Figure A12: Idiosyncratic stochastic volatilities.
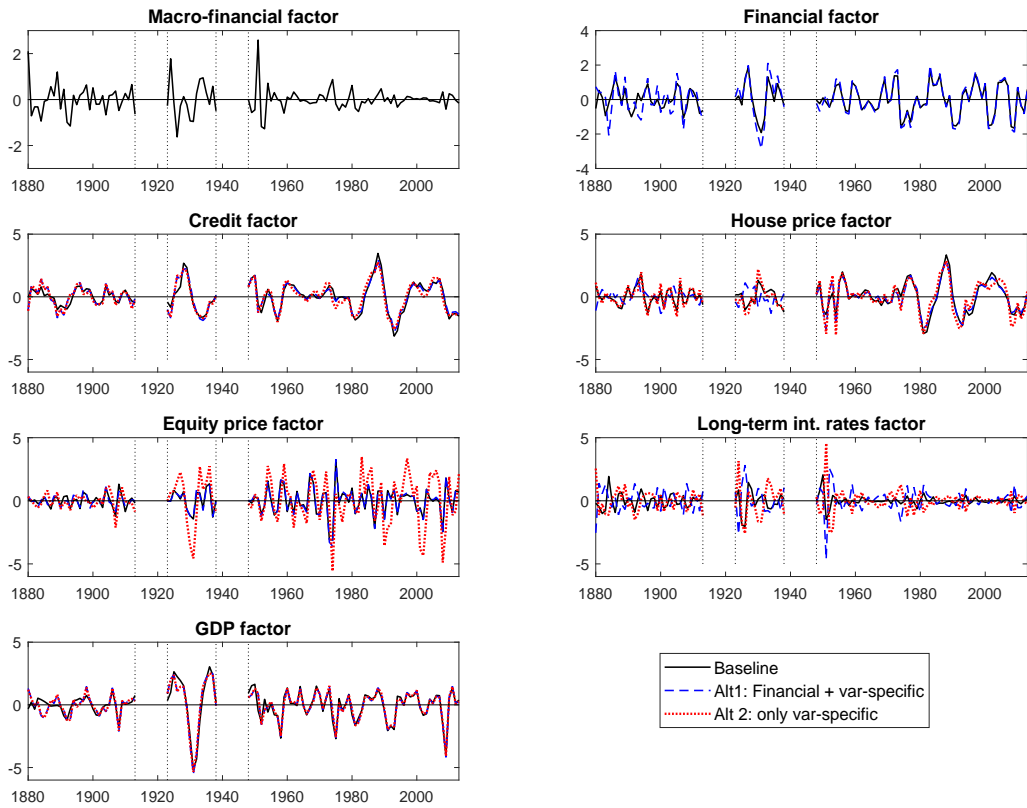Notes: Estimated with the hierarchical TVP DFM. Credibility sets not presented for readability.

Figure A13: 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.
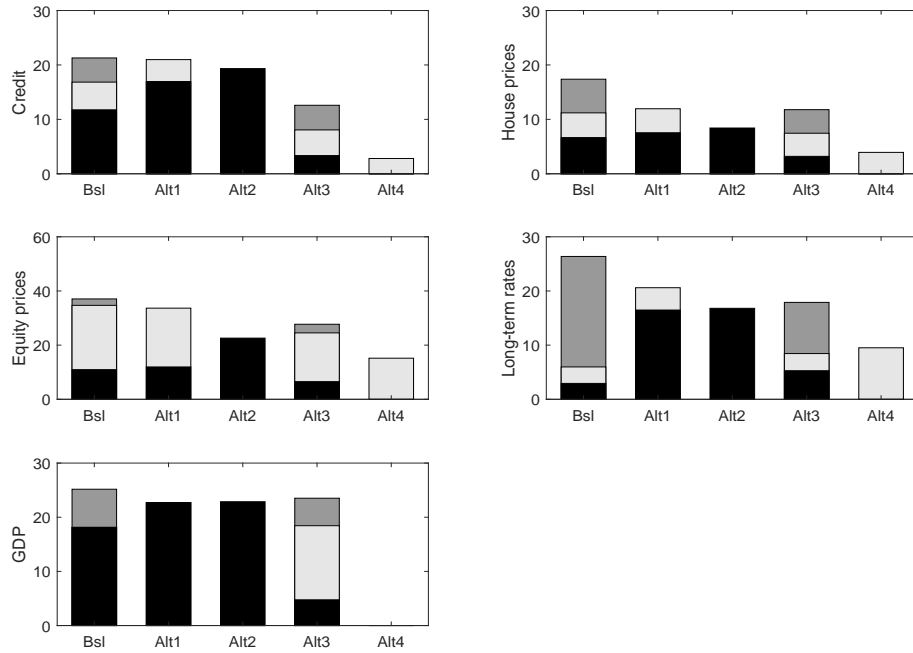
Figure A14: Explained variance shares, sensitivity to alternative factor structures.
Notes: Shares of variances explained by common factors, averaged over time and countries, medians over 500 retained Gibb draws. Bsl: Baseline, 3-level model with macro-financial factor (dark gray), financial factor (light 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).
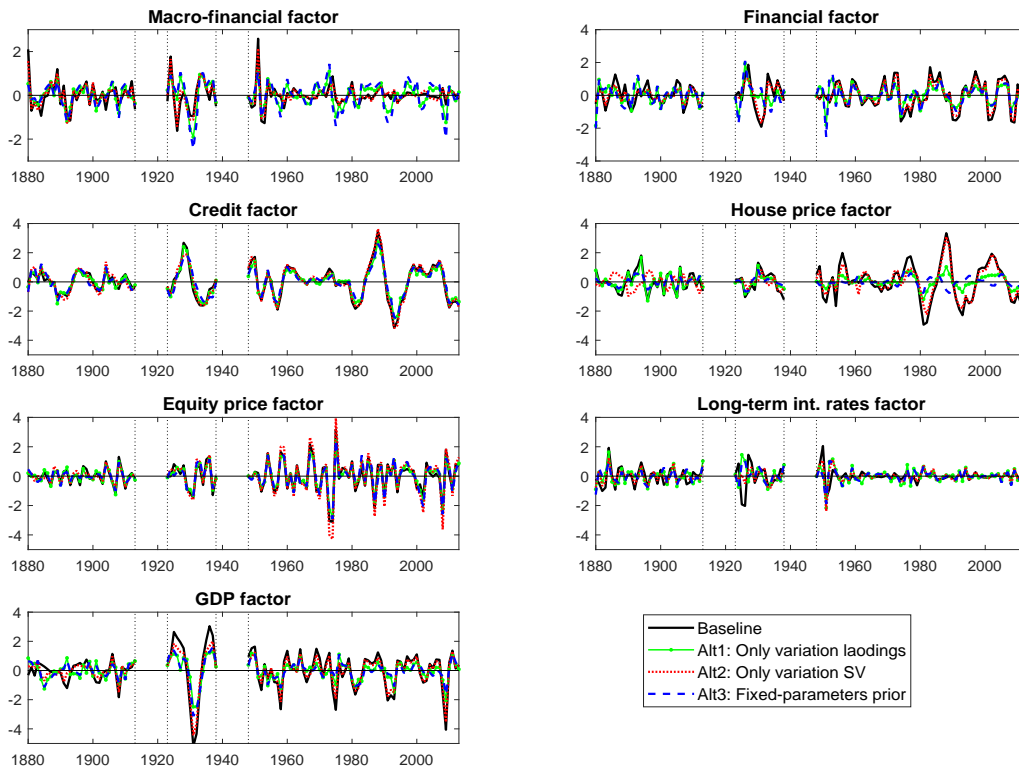

Figure A15: Global factors, sensitivity to alternative prior choices.
Notes: Common factors, medians over 500 retained Gibb draws. Baseline: Model with time-variation in loadings and stochastic volatilities. Alt1: Time-variation in loadings only. Alt2: Time-variation in stochastic volatilities only. Alt3: No time-variation (fixed parameters).
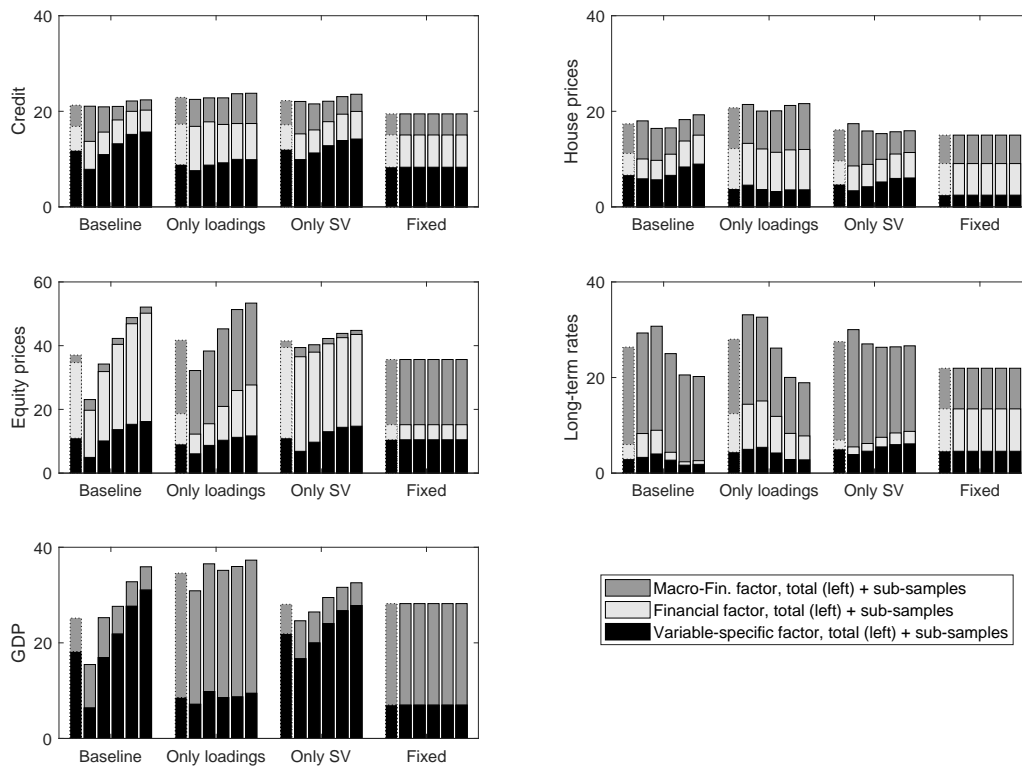
Figure A16: Explained variance shares, sensitivity to alternative factor structures.
Notes: Shares of variances explained by common factors, averaged over countries, medians over 500 retained Gibb draws. Total sample period (left bar) and sub-samples: 1880-1913 (2nd left bar), 1923-1938, 1948-1983, 1984-1998, 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).