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Evidence from Systemic Economies

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Abstract

The study estimates aggregate financial cycles and segment-specific cycles for credit, equity, bond and housing markets of the USA, the UK, Germany and Japan over the period 1960-2015 using dynamic factor models with state-space techniques based on a range of variables conveying market price, quantity and risk dynamics. The analysis reveals a highly persistent and recurring nature of financial cycles reflecting the build-up of financial imbalances in each segment with an estimated average cycle duration of about ten years. The significant co-movements and spillovers that we find among many of the segment-specific cycles suggest that well-diversified financial systems are prone to the risks associated with the mutual amplification of nominal shocks via linkages between financial market segments, which needs to be taken into account in the design of policies addressing asset bubbles and financial imbalances.

Keywords: financial cycles, asset bubbles, financial stability, housing prices, equity, debt securities, credit, capital markets, spillovers, Kalman filter, factor models

JEL classification: E44, E50, F37, G15

Contents

1 Introduction

The recent global economic crisis has revealed major weaknesses in the modern macroeconomic paradigm and stressed the need to enhance our understanding of the role of financial factors in economic growth and business cycles. The increasing complexity of financial systems and their cross-country interconnectedness carries serious risks for global economic growth and its stability as disruptions even in narrow financial market segments of individual economies may lead to a devastating impact on economies worldwide. Predictably, the debate on the finance-growth nexus has received additional impetus in the aftermath of the crisis and reached new levels as the need to revisit the current approach to macroeconomic policy with more attention paid to financial sustainability issues has been widely acknowledged, especially in the context of systemically important economies and cross-country spillovers[1], calling for additional research in these areas to support policy formulation.

As discussed in more detail in the next section reviewing the relevant literature, the importance of deep financial markets for facilitating economic growth and development has been well-investigated; however, the role of the financial system as a *driver* of business cycles has received much less attention. It appears that the effect of finance on growth is non-linear, and large and overheating financial markets are prone to inherent risks for macroeconomic stability related to continuous credit and debt expansions fueled by loose monetary and fiscal policy, a fractional reserve system, misperceptions of risk by market participants and income inequality giving rise to excess liquidity and boom-bust cycles in financial markets, and therefore play a much greater role in economic growth than previously recognized. This sharply contrasts with the notion of the "Great Moderation"[2] and demands changes to be made in monetary policy to address the issues associated with financial instability in a more comprehensive and effective way.

The paper presents new empirical evidence on the build-up of financial imbalances and focuses on the identification of aggregate financial cycles and cycles specific to the key financial segments—credit, housing, equity and debt securities markets—in the USA, the UK, Germany and Japan over the period 1960Q1–2015Q4. These countries represent a particularly interesting case for an in-depth assessment for a number of reasons. They are widely viewed as systemically important, i.e. having a high capacity to influence developments in the world economy,[3] and therefore zooming in on their financial systems

[1] In particular, major international economic institutions have expressed growing concerns about these issues, which is reflected in their flagship reports, e.g. IMF (2015), World Bank (2015), BIS (2014, 2015).

[2] The period of relative macroeconomic stability from the mid-1980s to 2007, often attributed to successful monetary policy, see more in Bernanke (2012), Stock and Watson (2003).

[3] These countries also top the list of countries with systemically important financial sectors identified by the IMF for the purposes of mandatory monitoring under its Financial Sector Assessment Program; see IMF(2010).

is instrumental for understanding related macroeconomic stability issues in a more general global context. Besides this, the selected countries have deep financial systems with sufficiently long statistical data available for each financial market segment with a well-documented history of financial distress episodes. Finally, two of the countries we focus on—the UK and the USA—are recognized as market-based financial systems, meaning that capital markets play an important role in channeling savings to investments, whereas Germany and Japan are viewed as bank-based systems, which rely more on traditional financial intermediation via banks.

The study employs a range of empirical techniques to estimate and analyze segment-specific and aggregate financial cycles for the countries in the sample. Each financial cycle index is constructed as an unobserved common factor derived from variation in a range of relevant standardized quarterly variables pertaining to the key properties of financial markets that have high signaling content in the context of asset bubble detection, which we organize into three categories—"Price", "Quantity" and "Risk". In line with the conjecture that cyclical movements across financial variables are largely driven by a single common factor, we extract financial cycles as the first latent factor (explaining most of covariance across the signal variables describing a particular financial segment or the entire national financial system in the case of aggregate cycles) via the Kalman filter and smoother applied to the state-space representation of a dynamic factor model. We also estimate non-stationary versions of financial cycles using the diffuse Kalman filter with quasi-maximum-likelihood estimation to measure their evolution along long-run time-varying trends. The estimated financial cycle measures are further decomposed into a smoothed medium-term cycle and a long-run trend components via the Hodrick-Prescott filter, followed by identification of turning points and phase/cycle duration using the Harding and Pagan (2002) BBQ algorithm.

The estimated segment-specific and aggregate financial cycles demonstrate high persistence with the autoregressive parameter above 0.7, which is consistent with the expectations about the self-reinforcing nature of financial cycles and accumulation of financial imbalances. The cycles also tend to exhibit strongly recurring boom-bust dynamics with rather regular cyclical patterns: in particular, financial cycles tend to fluctuate around long-run trends at an average frequency of about 10-11 years with an average phase duration of 4-5 years. While the estimated financial cycles capture the key past episodes of financial distress rather well, notably, our analysis also hints at a possible build-up of unsustainable dynamics as of 2015 across all financial markets in the USA, as well as in the housing markets in Germany, the UK and Japan. The chronology of phase sequencing suggests that these markets may be entering a contraction phase (bubble burst or a more protracted bear-market adjustment) in the next 1-3 years as of end-2017 given that similar expansionary tendencies continued to prevail in these markets after 2015–the last year of our empirical analysis.

The study then examines synchronization and dynamic interactions between financial cycles within each country based on phase concordance indexes, correlations and VAR models incorporating credit, housing, debt securities and equity cycles. Empirical results reveal nontrivial interdependence among many segment-specific cycles, particularly strong in the case of the USA. In particular, credit cycles are strongly affected in the USA and Germany by shocks in all other financial market segments, which is however not the case in the UK and Japan. In all four countries the bond market cycle (combining both government and corporate bonds) appears to Granger cause the housing market cycle at least at the 5%-level of statistical significance. Equity cycles appear to be relatively more decoupled from other segments: Granger causality results indicate a significant robust response to shocks only in the case of the USA housing market cycle.

The paper contributes to the literature in several ways. First, we identify both segment-specific and aggregate financial cycles. Most literature dealing with financial cycles is only concerned with credit cycles (for instance, Aikman et al. (2015), Dell'Arriccia et al. (2012), Schularick and Taylor (2012)), or, in a few cases, private credit variables are combined with housing prices to arrive at an aggregate measure (e.g. Borio (2014) argues that credit and housing price dynamics together constitute the most parsimonious description of financial cycles). At the same time, other financial market segments are largely neglected in the construction of an aggregate index. Besides identifying phases and cycles, we also analyze synchronicity and spillovers between segment-specific financial cycles and hence also fill this gap in the empirical research literature.

Second, our approach to estimating financial cycles is based on the extraction of an unobserved common factor from a large number of relevant variables characterizing market activity via a dynamic factor model, in contrast to the literature relying on a proxy variable, weighting of several variables or principal components analysis which assumes a static common factor.[4] The benefits of dynamic factor models allowing to model explicitly the persistent structure of the financial imbalances in contrast to static factor models have been recognized and similar approach is used in more recent works, e.g. in Hatzius et al. (2010) and Ng (2011). However, the focus of these studies is on monetary conditions, while we complement the literature by taking a more comprehensive, focusing both on credit dynamics and asset bubbles in the housing and capital markets.

Furthermore, whenever possible given data availability, we investigate each segment taking into account key market attributes (grouped in "Price", "Quantity" and "Risk" categories) that have high signaling properties for the identification of unsustainable dynamics, and try to incorporate the variables belonging to each category in a balanced way, which, in addition to standardization applied prior to estimations, allows for a

[4] For instance, in an interesting contribution Claessens et al. (2012) explore cyclical patterns in credit, equity and housing markets; however, the analysis is based on one proxy variable per each segment (credit, equity and housing prices), whereas our approach relies on aggregation of information contained in a multitude of variables.

symmetric treatment of each variable regardless of its measurement scale and volatility. That should result in a higher quality of financial cycle estimates in comparison with the widely used methods that only focus on asset price dynamics or incorporate a possibly larger number of financial variables without treatment of their underlying characteristics, which may bias the aggregate cycle estimates.

Next, while our framework takes into account certain methodological and conceptual recommendations in the literature, e.g. Borio (2014), Drehman et al. (2012), Hatzius et al. (2010), Stremmel (2012), it is less restrictive as we, whenever possible, do not impose constraints in the model estimation and filtering procedures that can alter the properties of financial cycle estimates, but rather allow the data to speak freely. *Inter alia*, we do not assume any symmetry or regularity in the cycles or phases, as well as duration thresholds, and analyze financial fluctuations at various frequencies. By contrast, it is common in the recent literature on financial cycles that slow-moving dynamics of financial cycles are *a priori* imposed by the methodology: in most cases by means of statistically filtering out only low-frequency components of asset prices or other variables, which deliberately forces the cycles to be slow-moving and may omit relevant information contained in the dynamics at higher frequencies at least for some countries.[5] In fact, our results suggest that financial cycles have a duration of approximately 10 years, which is shorter than the estimates in Borio et al. (2012) and Drehman et al. (2012), where cycles are extracted as a slow-moving component from private credit and housing price dynamics and are reported to have an average duration of 16 years. We also derive both stationary and non-stationary cycles, while the literature has been concerned to date only with the former case. This allows to capture the evolution of time-varying trends and longer cycles, as differencing the data to arrive at stationary series leads to a loss of potentially important information.

Finally, the paper contributes to the literature discussing financial structure and relative merits of bank-based versus market-based financial systems. We add to the debate by offering new empirical evidence from the perspective of financial cycles, related segment-specific imbalances and their interactions.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 discusses the conceptual framework behind our financial cycle measures. Section 4 describes the methodology and data. Section 5 presents empirical results. Section 6 discusses policy implications. Section 7 concludes.

[5] A similar argument is put forward in Schüler et al. (2015). The study uses a multivariate spectral approach to identify financial cycles for selected advanced EU economies and suggests that fluctuations at shorter frequencies are also important.

2 Literature review

The paper is most closely related to several strands of economic literature that analyze asset bubbles, cyclical dynamics in financial markets and their implications for macroeconomic stability. The entire pool of research on the finance-growth nexus is immense and a detailed discussion is beyond the scope of the study. In general, the importance of financial markets for economic growth and development was emphasized as early as in Schumpeter (1911), Goldsmith (1969), McKinnon (1973) and Shaw (1973). In the more recent literature the relationship between financial depth and economic growth has been well investigated empirically using cross-country analysis with a typical finding that financial deepening is associated with higher economic growth (see, e.g. Beck and Levine (2004), Beck et al. (2000), Beck (2008), Demetriades and Hussein (1996), King and Levine (1993), Levine (1997), Levine and Zervos (1998), Rousseau and Wachtel (2011)). As regards a formalized framework, the literature has been mostly modeling and studying the linkages between the financial sector and the real economy in the context of financial frictions that amplify disturbances in stemming from macroeconomic fundamentals (Bernanke and Gertler (1989), Bernanke et al. (1999), Brunnermeier and Sannikov (2014), Carrillo and Poilly (2013), Christiano et al. (2005), Kiyotaki and Moore (1997)).

However, as argued for instance in Borio et al. (2013), Borio (2014), Woodford (2010), the conventional approach reducing the impact of financial factors to nominal frictions that only marginally affect the speed of business cycle adjustments to equilibrium in an otherwise stable economy, has proved to be overly limiting as it ignores the role of finance as an important force *per se* driving the real economy. The idea of broad cyclical movements in financial markets associated with recurrent imbalances is certainly not new and goes back at least to the famous financial instability hypothesis of Minsky (1978, 1982) and further elaboration on the drivers and stages of the build-up of financial market imbalances in Kindleberger (1978). Not surprisingly, as a result of the global financial crisis and failure of established macroeconomic models to foresee it, research focusing on the analysis of financial cycles as broad cyclical movements in investors' sentiment and risk perceptions underpinning fluctuations in financial market activity with potentially significant effects on business cycles, echoing these works in many respects, has received increasing attention. In particular, a growing body of empirical literature has been concerned recently with the documentation of the existence and significance of financial cycles in different countries (Aikman et al, (2015), Borio (2013, 2014), Borio et al. (2013, 2014), Claessens et al. (2011, 2012), Drehmann et al. (2012), Nowotny et al. (2014), Schüler et al. (2015), Schularick and Taylor (2012), Stremmel (2015)). These contributions, *inter alia*, note a generally much lower frequency of financial cycles in comparison with business cycle fluctuations, as well as their close association with financial crisis episodes. Related to this research is the strand of literature focusing on financial conditions or financial stress indexes (for a detailed review of the literature see, e.g. Hatzius et al. (2010)). However, the emphasis of this research is on practical applications of these indexes as monitoring and forecasting tools, typically concerned with credit conditions and monetary policy transmission.

In light of growing economic interdependence between countries, the hypothesis of cross-country spillovers of financial cycles and existence of a global financial cycle has also gained popularity. The existence of a global financial cycle driven largely by the monetary conditions in a few systemically important economies along with changes in global risk perceptions has been tested empirically (Bekaert et al. (2012), Bruno and Shin (2014), Cerutti et al. (2017), Miranda-Agrippino and Rey (2015)). For instance, Miranda-Agrippino and Rey (2015) report that about a quarter of price variation in a large cross-country sample of risky assets examined in the paper can be attributed to a common global factor, and in Rey (2015) it is shown that it can be well approximated by the dynamics of the CBOE Volatility Index VIX. In Gerko and Rey (2017) the phenomena is further linked to the transmission of monetary policy in two systemically important economies—the USA and the UK. This relates to a more general literature on co-movement tendencies in financial markets and cross-country spillovers of shocks via financial linkages (Aizenman et al.(2015), Backe et al. (2013), Calvo et al. (1996), Eichengreen and Portes (1987), Nier et al. (2014), Obstfeld (2012), Obstfeld and Rogoff (2010), Reinhart and Reinhart (2009)) and the dominant role of financial developments and monetary policy in advanced economies in this (Adrian and Shin (2010), Bekaert et al. (2012), Bruno and Shin (2014, 2015)).

In light of the evidence on the implications of financial cycles for the stability of economic growth, attempts have been made recently to revisit the conventional approach to the estimation of output gaps so far predominantly relying on the idea of non-accelerating inflation as the key price variable signaling about macroeconomic sustainability, and introduce also asset prices or other financial variables to the estimation procedure (Banternghansa and Peralta-Alva (2009), Bernhofer et al. (2014), Borio et al. (2014), Grintzalis et al. (2017)), as well as to formalize financial cycles in a general macroeconomic equilibrium framework (Coimbra and Rey (2017)).

Finally, our paper also partially concerns a distinct body of literature that focuses on the relative merits of financial structure—the composition of agents and institutions providing financial intermediation— and identifies bank-based and market-based financial systems: e.g. Boyd and Smith (1998), Demirgüç-Kunt and Levine (1999), Levine (2002), Tadesse (2002), Langfield and Pagano (2015). Empirical studies along this avenue of research suggest that both systems can fulfill the role of growth engines provided they are sufficiently large and efficient, as well as point out complementarities between the development of different financial segments. In particular, Demirgüç-Kunt et al. (2013) suggest that the role of different financial segments evolves along with economic development, and as countries advance economically, capital markets tend to become relatively more important than banks.

3 Definition of financial cycles and taxonomy

In the first place, it is important to specify precisely what is meant by financial cycles as there is so far no commonly accepted conceptual framework and the literature is rather vague when it comes to the definition of financial cycles, often attaching rather differing meanings to the phenomenon.[6] We define financial cycles as cyclical movements of activity in financial markets around respective long-run equilibrium trends, which are associated with the build-up of imbalances followed by corrections to equilibrium levels. The accumulation of imbalances manifests itself as excessive risk-taking behavior and related continued increase in market activity and asset prices beyond sustainable levels.

This description is equally applicable to aggregate financial systems as well as specific financial market segments, and at the same time is not restrictive in the sense that it does not imply any particular duration, frequency, symmetry or other regularities of financial cycles beyond their boom-bust nature. It is also consistent with the widely cited description of financial cycles as "self reinforcing interactions between perceptions of value and risk, attitudes towards risk and financing constraints, which translate into booms followed by busts" in Borio (2012). However, our definition is more general as it is agnostic about the specific drivers of cyclical movements, but rather focuses on the resulting manifestation of interactions between a variety of demand and supply factors in financial markets not necessarily limited to perceptions of risk and value.

In the study we distinguish the following four segment-specific financial cycle measures and an aggregate financial cycle[7] estimated for each country (v denotes a version of the cycle, discussed in the methodology section):

- **Credit market cycle** $FC_{CR}^{(v)}$**:** captures activity in the banking sector and overall monetary conditions conveyed by such variables as private credit volume (relative to GDP and year-on-year growth rates), short-run and long-run interest rates, monetary aggregates, the volume of financial deposits and banking system assets, interest rate spreads (maturity, lending-deposit, etc.).

[6] In many cases by financial cycles the literature assumes only credit cycles and general monetary conditions, albeit in the more recent studies the housing market is also taken into consideration. It is less common, however, to consider capital markets in the context of financial cycles, and, for instance, the stock market is deliberately dropped from the analysis of aggregate financial indexes as introducing irrelevant noise (Drehman et al. (2012)).

[7] In this regard, we limit our analysis only to the four financial segments that have been historically most important and have long statistical data available for a meaningful analysis. This also implies that the aggregate financial cycle, while being a more complete index than the literature has offered so far, is yet not a truly comprehensive measure, as it does not cover a range of other relevant markets, e.g. derivatives, foreign exchange, commodity markets.

- **Housing market cycle $FC_H^{(v)}$:** reflects residential property price and mortgage dynamics, price-to-rent and price-to-income ratios, mortgage rates.

- **Bond market cycle $FC_B^{(v)}$:** conveys general dynamics in national debt securities markets (both government and corporate bonds), including yields and spreads, amounts outstanding (as a share of GDP and year-on-year growth rates).

- **Equity market cycle $FC_{EQ}^{(v)}$:** captures equity market conditions as conveyed by national benchmark stock market indexes, returns on the indexes and their volatility, stock market capitalization and turnover ratios.

- **Aggregate financial cycle $FC_{AG}^{(v)}$:** a broad-based index reflecting the overall dynamics of national financial markets based on common variation across the four financial segments listed above.

The general logic of the boom-bust movements in financial markets has been well discussed in the literature. Optimism of economic agents about future overall macroeconomic and sector-specific developments, or merely their speculative expectations of price growth in a particular asset class, may lead to excessive risk undertaking in investment and borrowing activity. This can be further aggravated by supply-side developments if liquidity is ample and lending standards deteriorate as risk perceptions of lenders also become loose. Stimulated by higher demand, rising asset prices in turn boost the market value of collateral, thus facilitating further credit expansion (the wealth channel, see Bernanke and Gertler (1995)). After asset bubbles burst eventually, the financial cycle enters a contraction phase associated with the hectic sell-off of problematic overpriced assets at discount ("fire sales") accompanied by heightened volatility and plummeting prices, balance sheet problems of banks, a general loss of confidence in the financial system, further amplifying the panic (see also Claessens et al. (2011), Kaminsky and Reinhart (1999), Reinhart and Rogoff (2009, 2011)).

Taking into account these stylized facts, we try to capture the cyclical dynamics in each of the financial sectors examined by organizing the available variables around three key market characteristics we believe are critical for the identification of unsustainable tendencies: *Price–Quantity–Risk*. Under this framework, the market attribute labeled *"Price"* captures price dynamics (interest rate in the case of credit markets) in absolute or relative terms (e.g. price-to-income ratios in the housing market) or returns on a particular asset class; *"Quantity"* variables pertain to various nominal measures of the overall volume of market activity in the segment, e.g. amounts outstanding of securities (year-on-year growth rate or in relative terms, e.g. as a share of GDP), market capitalization, turnover, claims on the private sector by banks, etc.; *"Risk"* combines variables conveying the perceptions of risk and volatility, e.g. interest rate spreads, volatility of returns.[8]

Financial cycles can then be quantified by means of a single index summarizing systematic patterns that the variables pertaining to these three market attributes exhibit during expansions and contractions of activity in financial markets (we do this via a dynamic factor model). Using information contained in a variety of financial variables structured into the three "pillars" and distinguishing between financial segments should allow for a more precise estimation of financial cycles. This contrasts with the studies that rely on a single or several proxy variables, which may not appropriately capture relevant market developments or entirely omit some financial segments[9] or studies that use a similar common-factor based approach, but use a large number of financial variables without balancing them in terms of signalling particular market characteristics, which may potentially bias the results by overrepresenting in an aggregate index certain market aspects (e.g. asset prices), while ignoring the other (e.g. volume and risk measures).

4 Methodology

4.1 State-space model for financial cycle derivation

Various methodologies have been used in empirical research literature to derive financial cycles or estimate aggregate monetary conditions indexes, including identification of turning points to track the dynamics of selected signal variables (Claessens et al. (2011)), frequency-based statistical filters (Drehmann et al. (2012)), spectral analysis (Strohsal et al. (2015), Schüler et al. (2015)), principal components and dynamic factor models (Brave and Butters (2011), Eickmeier et al. (2014), English et al. (2005), Hatzius et al. (2010)).[10]

In terms of economic information content, financial cycles are typically approximated by a variable deemed to be most relevant (as a rule, private credit as a share of GDP is used as a proxy, in some cases complemented by asset prices), or, alternatively, evolution of several relevant series is aggregated using weighting schemes or more complicated methods relying on extracting common unobserved factors. The latter approach appears to be more promising as a single proxy variable has only limited signaling power and may thus result in biased estimates.

[8] This approach comes close to Jones (2014), in which it is argued that asset bubble diagnostics should be organized around the "pricing" and "quantities" pillars. Under our approach we however also distinguish a "risk" pillar as it may better convey the dynamics associated with *speculative*, as opposed to *fundamental* drivers of financial market activity, and opt for a model-based extraction of common factors rather than descriptive diagnostics based on a range of observable variables as in Jones (2014).

[9] For instance, private credit to GDP ratio often used as a proxy for financial conditions does not necessarily pick up information about risk perceptions and interest rates, and is entirely agnostic about conditions in capital markets

[10] For additional discussion of methods used for constructing financial conditions indexes one can also review Hatzius et al. (2010).

Owing to the logic discussed in the previous section that a financial cycle represents a single common factor driving activity across a financial market segment of a country (or all financial segments in the case of aggregate cycles), manifesting itself as regular correlated cyclical patterns of market activity and prices, we estimate aggregate synthetic financial cycle indicators by means of a dynamic factor model. Dynamic factor models are constructed separately for each financial market segment of a given country to derive a financial cycle index as a common unobservable factor from a possibly large number of relevant quarterly financial variables characterizing the dynamics of that segment.

In general, factor models[11] rest on the idea that covariance between a wide range of observed variables can be spanned by a much smaller number of unobserved orthogonal common factors. Put in the context of financial cycles, the vector of observable variables (or measurement/signal variables in the language of state-space models) describing various characteristics of a given financial market segment, $\mathbf{y}_t = [y_{1t} \ldots y_{Nt}]'$ for $t = 1 \ldots T$, is modeled as the sum of unobservable common factors and idiosyncratic shocks, written in a state-space representation as follows:

$$\begin{cases} \mathbf{f}_t = \mathbf{A}\mathbf{f}_{t-1} + \mathbf{e_t} \\ \mathbf{y}_t = \mathbf{B}\mathbf{f}_t + \mathbf{v_t} \end{cases} \tag{1}$$

where $\mathbf{f}_t$ is a $k \times 1$ vector of unobserved state variables—“factors” that capture the common variation in $\mathbf{y}_t$ extracted via maximum likelihood estimation; the factors $\mathbf{f}_t$ are assumed to follow a dynamic process determined by the coefficient matrix $\mathbf{A}_{k\times k}$; $\mathbf{B}_{N\times k}$ is the matrix of factor loadings (observation matrix) summarizing exposures of each financial variable to the common factors, s.t. $k < N$; the vector $\mathbf{y}_t$ is composed of N input signal variables conveying price, risk and quantity characteristics of a market; $\mathbf{e_t}$ and $\mathbf{v_t}$ are the disturbance vectors assumed to be identically and independently normally distributed with the covariance matrices $cov(\mathbf{e_t}) = \mathbf{Q}$; $cov(\mathbf{v_t}) = \mathbf{R}$; $cov(\mathbf{e_t}, \mathbf{v_t}) = 0$.

In our case $\mathbf{f}_t$ comprises only one factor as the objective of the study is to identify a single common factor that drives dynamics of financial activity and is thus correlated across observable variables of $\mathbf{y}_t$.[12] The financial cycle is expected to be a highly persistent process, capable of generating self-reinforcing accumulation of imbalances. Therefore, we opt for a dynamic representation of the unobserved factor (in contrast to a static factor

[11] Dynamic factor models were originally introduced in Geweke (1977) and Sargent and Sims (1977). For a recent review of the methodology and applications see Stock and Watson (2011).

[12] It is certainly possible to derive multiple factors that would jointly explain more variation in the data, which would be useful for forecasting individual financial series. However, our goal is to estimate a single most relevant factor. Furthermore, the dynamic factor model is used as a dimension reduction method to shrink financial market information contained in multiple series, and thus it does not make sense to replace the original variables with several factors, especially owing to the fact that the list of available variables with sufficiently long time series is often rather limited.

assumed in the principal component analysis), described most parsimoniously as an AR(1) process in Equation 1.[13]

Prior to entering a state-space model all observable variables are standardized – demeaned and divided by their sample standard deviation. This ensures that the variance of individual input variables and hence their signaling properties contribute to the dynamics of the common factor symmetrically, and the differences in their measurement scale and magnitudes do not bias the estimates. Other transformations applied to the measurement variables involve differencing the data (year-on-year percentage change or percentage-point change, depending on the nature of a variable).[14] Unit root tests (Augmented Dickey-Fuller and Phillips-Perron tests) are performed for all variables that enter the model and the null of a unit root is in most cases rejected for the transformed series used in the construction of stationary versions of financial cycles.[15]

For model parameter estimation we resort to the Kalman filtering techniques with maximum likelihood estimation for stationary models and the diffuse Kalman filter with quasi-maximum likelihood in line with De Jong (1988, 1991) for non-stationary versions of the model.[16] In brief, the Kalman filter recursively derives log-likelihood of the observed variables conditional on their past values to form linear predictions of the current state values (for brevity the exposition of recursions is omitted in the paper; see Hamilton (1994) for the derivation and description of recursions, as well as a general discussion in economic contexts). Unlike conventional dynamic factor models, the Kalman filter allows for non-stationary models to be estimated and is capable of addressing gaps in series thereby also tackling the "jagged" edge data issues.[17]

The parameters of a state-space model are under-identified in the absence of additional restrictions (see Harvey(1989) and Hamilton(1994)), and the set of parameter values for a particular value of the likelihood function used in the Kalman filtering process is not unique.[18] Hence, to aid identification, we constrain $\mathbf{Q}$ to be the identity matrix and $\mathbf{R}$ to be a diagonal matrix with equal variances along the main diagonal. Given that the input variables are all standardized and the estimated common factor itself does not have a

[13] Other lag order models (up to four lags) were also fitted for robustness. Simple AR(1) representation however delivers the best results and is also helpful for parameter identification.

[14] Differencing the data to ensure stationarity may erode meaningful information contained in the dynamics of the series in levels, as also noted in Angelopoulou et al. (2014) and English et al. (2005). Therefore, in addition to stationary we also estimate non-stationary versions of financial cycles using the data in levels.

[15] In some cases, when the differenced variables remain non-stationary or only weakly stationary, we still use them in the model with the quasi-maximum likelihood estimation so that the same variables with the same transformations are used consistently across the countries, data permitting.

[16] It is shown in Hamilton(1994) that the quasi-ML estimator for models where the normality and stationarity assumption does not hold is still consistent and asymptotically normal.

[17] In such cases recursions proceed by estimating the state based only on the measurement variable data de facto available for that period.

[18] In particular, using any non-singular matrix $\Psi_{k\times k}$, it is possible to arrive at a model equivalent to Equation 1 by transforming it s.t. $\mathbf{B}^* = \mathbf{B}\Psi^{-1}$, $\mathbf{A}^* = \mathbf{A}\Psi^{-1}$, $\mathbf{f}_t^* = \Psi\mathbf{f}_t$

direct economic interpretation and is also scale-irrelevant (what matters is the dynamics, the length of phases and their relative sample magnitudes), this should not bias inference. To address such scale indeterminacy issue associated with the estimated financial cycle measure we standardize it so that the magnitudes could at least be interpreted in terms of standard deviations from the sample mean.

Finally, the remaining issue of sign indeterminacy is addressed by rotating the common factor so that the reference segment-specific observable variable has a positive factor loading in the respective estimated model. The reference variables we use are the indicators typically employed in the literature to gauge the dynamics in a particular sector: the ratio of private credit to GDP for $FC^{(v)}_{CR}$ and $FC^{(v)}_{AG}$; real housing price index for $FC^{(v)}_{H}$; yield on 3-month government securities for $FC^{(v)}_{B}$; national stock market index for $FC^{(v)}_{EQ}$. As already noted, this implies that the estimated financial cycle for the debt securities market moves in the direction opposite to implied bond price level as the latter is inverse to its yield. At the same time, financial cycles for the equity and housing markets co-move with their respective general price levels. The credit cycle expansion reflects loosening of monetary conditions and vice-versa.

4.2 Dissecting financial cycles into gaps and trends

In order to extract smoothed cyclical components and long-run trends from the estimated financial cycle indexes, we resort to the Hodrick-Prescott (HP) filter set up as follows:

$$\min_{\eta} L = \sum_{t=1}^{T} \left[\frac{(FC_t - \eta_t)^2}{\sigma_0^2} + \frac{(\Delta\eta_{t+1} - \Delta\eta_t)^2}{\sigma_1^2} \right], \text{ where } \lambda = \sigma_0^2/\sigma_1^2 = \begin{cases} \text{(a) } 1600 & \text{for medium-term cycle} \\ \text{(b) } 400000 & \text{for long-term trend} \end{cases} \quad (2)$$

The smoothing parameter value λ=1600 in Case (a) is the standard value used for quarterly data; λ=400000 in Case (b) is chosen to estimate long-run time-varying trends.[19]

We further refer to the HP-filtered versions of financial cycles with $\lambda = 1600$ as the "smoothed medium-term" cycles denoted as $FC^{*(v)}_{CR}$, $FC^{*(v)}_{EQ}$, $FC^{*(v)}_{B}$, $FC^{*(v)}_{H}$, $FC^{*(v)}_{AG}$. The HP-filtered series with $\lambda = 400000$ dubbed "long-run trends" are similarly denoted as $\overline{FC}^{(v)}_i$, $i = CR, EQ, B, H, AG$. The "gap" versions of financial cycles are then computed as deviations from the long-run trend of the raw financial cycle measure ($\widehat{FC}^{(v)}_i = FC^{(v)}_i - \overline{FC}^{(v)}_i$) and its smoothed medium-term counterpart ($\widehat{FC}^{*(v)}_i = FC^{*(v)}_i - \overline{FC}^{(v)}_i$).[20]

[19] The value of 400000 for HP filtering is also suggested in Borio et al. (2012) and Drehman et al. (2012) as the optimal value to derive long-run financial cycles from the proxy variable (private credit to GDP ratio). However, we apply this to the estimated financial cycle measure (which is by itself a filtered measure) rather than raw financial series, thus the interpretation is different. Other time-series filters and alternative signal-to-noise ratio values were examined for robustness.

[20] While it might not be necessary for the "stationary" versions of financial cycles ($v = 1, 3$), we nevertheless compute and analyze trends and gaps for them also given that they tend to exhibit high persistence and in some cases may include non-stationary or weakly stationary input variables.

4.3 Identification of phases and their synchronicity

For the identification of the turning points and phases of the estimated and smoothed financial cycles we employ the BBQ algorithm, which is a Harding and Pagan (2002) quarterly (hence, “Q”) implementation of the original Bry and Boschan (1971) algorithm (“BB”) originally developed to date turning points for monthly frequency time series. The procedure identifies a peak/trough for a given variable at a date $t = \tilde{t}$ if the value of the variable at this date is higher/lower than that in any of the previous k and the following k periods, and also ensures that peaks and troughs alternate. We impose additional constraints on the search algorithm by restricting the minimal phase duration to 3 quarters and the minimal cycle duration to 6 quarters, so that the turning points (tp dummy) are identified as follows:

$$tp = 1 \text{ (peak) at } t = \tilde{t} \text{ if: } \begin{cases} \Delta FC_{\tilde{t}} > 0; \Delta FC_{\tilde{t}-1} > 0; \Delta FC_{\tilde{t}-2} > 0 \\ \Delta FC_{\tilde{t}+1} < 0; \Delta FC_{\tilde{t}+2} < 0; \Delta FC_{\tilde{t}+3} < 0 \\ \min |\tilde{t}_{peak} - t_{trough}| \geqslant 3 \text{ quarters} \end{cases} \tag{3}$$

$$tp = \text{-1 (trough) at } t = \tilde{t} \text{ if: } \begin{cases} \Delta FC_{\tilde{t}} < 0; \Delta FC_{\tilde{t}-1} < 0; \Delta FC_{\tilde{t}-2} < 0 \\ \Delta FC_{\tilde{t}+1} > 0; \Delta FC_{\tilde{t}+2} > 0; \Delta FC_{\tilde{t}+3} > 0 \\ \min |\tilde{t}_{peak} - t_{trough}| \geqslant 3 \text{ quarters} \end{cases} \tag{4}$$

The phase from a trough to the following peak we further denote as an “expansion” and the phase from a peak to the following trough—a “contraction”. Using the identified turning points, similar to Avouyi-Dovi and Matheron (2005) and Claessens et al. (2011), a concordance index CI is computed to gauge the similarity of phases of different cycles. To compute the CI index we first define a binary phase indicator $\phi_{FC_i,t}$ and $\phi_{FC_j,t}$ for financial cycles i and j:

$$\phi_{FC_i,t} \text{ (or } \phi_{FC_j,t}) = \begin{cases} 1 \text{ if } FC_i \text{ (or } FC_j) \text{ is in expansion at period } t \\ 0 \text{ if } FC_i \text{ (or } FC_j) \text{ is in contraction at period } t \end{cases} \tag{5}$$

The bilateral phase concordance index for cycles i and j is then calculated as:

$$CI_{ij} = \frac{1}{T} \sum_{t=1}^{T} \left[\phi_{FC_i,t} \phi_{FC_j,t} + (1 - \phi_{FC_i,t})(1 - \phi_{FC_j,t}) \right], \tag{6}$$

By construction, $CI_{ij} = 1$ if cycles i and j are perfectly aligned in terms of their phases over the history of observations, and $CI_{ij} = 0$ if they are always in opposite phases. The concordance index complements the conventional Pearson correlation indexes computed for the financial cycles expressed in gaps and first-differences to analyze the synchronization of segment-specific cycles.

4.4 VAR analysis of spillovers

In addition to the synchronicity analysis, we use the estimated financial cycle indicators to analyze the propagation of nominal shocks originating in each of the financial segment throughout the rest of the national financial system. The spillover analysis is performed via a stationary quarterly VAR model incorporating either the first-differences (Eq. 8) of the segment-specific financial cycles or their gap versions (Eq. 7) as follows:

$$\begin{bmatrix} \widehat{FC}_{CR,t} \\ \widehat{FC}_{H,t} \\ \widehat{FC}_{B,t} \\ \widehat{FC}_{EQ,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ c_4 \end{bmatrix} + \begin{bmatrix} b^k_{11} & b^k_{12} & b^k_{13} & b^k_{14} \\ b^k_{21} & b^k_{22} & b^k_{23} & b^k_{24} \\ b^k_{31} & b^k_{32} & b^k_{33} & b^k_{34} \\ b^k_{41} & b^k_{42} & b^k_{43} & b^k_{44} \end{bmatrix} \begin{bmatrix} \widehat{FC}_{CR,t-k} \\ \widehat{FC}_{H,t-k} \\ \widehat{FC}_{B,t-k} \\ \widehat{FC}_{EQ,t-k} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix} \tag{7}$$

$$\begin{bmatrix} \Delta FC_{CR,t} \\ \Delta FC_{H,t} \\ \Delta FC_{B,t} \\ \Delta FC_{EQ,t} \end{bmatrix} = \begin{bmatrix} c_{\Delta 1} \\ c_{\Delta 2} \\ c_{\Delta 3} \\ c_{\Delta 4} \end{bmatrix} + \begin{bmatrix} b^k_{\Delta 11} & b^k_{\Delta 12} & b^k_{\Delta 13} & b^k_{\Delta 14} \\ b^k_{\Delta 21} & b^k_{\Delta 22} & b^k_{\Delta 23} & b^k_{\Delta 24} \\ b^k_{\Delta 31} & b^k_{\Delta 32} & b^k_{\Delta 33} & b^k_{\Delta 34} \\ b^k_{\Delta 41} & b^k_{\Delta 42} & b^k_{\Delta 43} & b^k_{\Delta 44} \end{bmatrix} \begin{bmatrix} \Delta FC_{CR,t-k} \\ \Delta FC_{H,t-k} \\ \Delta FC_{B,t-k} \\ \Delta FC_{EQ,t-k} \end{bmatrix} + \begin{bmatrix} \epsilon_{\Delta 1,t} \\ \epsilon_{\Delta 2,t} \\ \epsilon_{\Delta 3,t} \\ \epsilon_{\Delta 4,t} \end{bmatrix} \tag{8}$$

where $k = 1...K$, the lag order K is selected based on conventional lag order selection information criteria.

Our strategy for the identification of orthogonal IRFs is based on the Cholesky decomposition of the error-covariance matrix with the ordering of the variables as specified in the VAR models: FC_{CR}, FC_H, FC_B, FC_{EQ}. Given the quarterly frequency of the data and the slow-moving persistent nature of financial cycles, our identification scheme is consistent with the monetary policy transmission literature. In particular, the ordering implies that asset prices are expected to react within the same period in response to shocks in the credit market (which also implicitly incorporates monetary policy reaction and transmission via neoclassical and non-neoclassical channels[21] as picked up by interest rates, spreads, nominal credit volume and banking sector conditions variables), whereas the reaction of credit to asset price dynamics may occur only with a lag. Adjustments in policy rates that further translate to credit dynamics typically occur only gradually and in response to persistent changes in asset prices rather than short-run transitory fluctuations. Housing purchases are generally financed by debt, at the same time higher housing prices may facilitate further borrowing through the wealth effect with a lag. Debt financing may apply to other assets as well, given the importance of leverage as an investment vehicle. In this regard financial securities are assumed to react faster in response to

[21] For discussion see, e.g. Boivin et al. (2010).

changes in liquidity and credit conditions relative to the housing market (housing prices are also more "sticky"). Finally, the equity market is assumed to accommodate much faster than the other financial segments to relevant shocks and have a greater speculative idiosyncratic component resulting in greater volatility, and hence is positioned last in the identification scheme. A similar logic for ordering variables in the VAR context is used in Alessi and Kerssenfischer (2016) and Goodhart (2008). For robustness, other orderings were also used. The IRF analysis is complemented by a series of Granger causality tests for the equations of the two VAR models constructed for each country in the sample to determine possible causal bilateral and joint effects between segment-specific cycles.

4.5 Data and country coverage

The analysis focuses on a sample of systemically important economies—the USA, the UK, Germany and Japan—over the period of 1960–2015 or the maximum period available for a given country-segment. As already noted, the USA and the UK are characterized by a more diversified financial market structure with a prominent role played by capital markets complementing a developed banking sector, and are classified in the literature on financial structure (e.g. Beck et al. (2000), Levine (2002)) as market-based financial systems. On the contrary, Germany and Japan rely more heavily on traditional forms of financial intermediation and are classified as bank-based financial systems. Each of the countries in the sample have well-documented episodes of financial distress, which allows to cross-check the validity of our financial cycle estimates. For each country we assemble a large dataset of financial variables at quarterly frequency from several publicly available sources:

- BIS financial and housing market databases: credit to households, non-financial corporations, and the private non-financial sector in general, debt securities (amounts outstanding), housing prices.
- IMF International Financial Statistics (IFS): private credit, interest rates and spreads, financial system deposits, deposit money bank assets, monetary aggregates in absolute and relative terms, government bond yields.
- OECD Main Economic Indicators and Housing Statistics: interest rates and spreads, volume of residential mortgages, real property prices, housing price to rent and price to income ratios, stock market index values, monetary aggregates.
- Federal Reserve Economic Data database (FRED): household mortgage rates, government and corporate bond yields and spreads, stock market index values.
- World Banks Global Financial Development Database (GFDD): bank credit to deposit ratios, private credit, amounts outstanding of private and public debt securi-

ties, stock market capitalization, stock market turnover ratio, stock price volatility.

- Investing.com or Yahoo Finance (YF) data: stock market index values, daily returns and their standard deviation.
- Haver Analytics and national sources (monetary authorities): mortgage rates and loans to households, yields on debt securities, monetary aggregates.

Nominal variables are taken in local currency units and as a percentage of GDP. Most of the data is already available at a quarterly frequency and seasonally adjusted when needed. Daily stock market index values were used to compute daily returns and their volatility for benchmark national stock market indexes (USA S&P500, GBR FTSE100, DEU DAX, JPN NIKKEI225) over the respective quarters. The variables reported at a monthly frequency were aggregated to quarterly series by averaging over the respective 3-month period. Annual data on financial structure from the World Bank's GFDD database were converted to quarterly via cubic spline interpolation and checked against proxy variables or equivalent variables available for a shorter period of time to ensure the validity of the method.

Breaks in certain series were also addressed when possible. In particular, the IMF IFS series associated with the identical/similar concept, but reported in the database under different codes for different periods was merged. For instance, private credit by banks variable was constructed from the IMF IFS data reported under codes *line 22d* and *FOSAOP*; depositary corporations claims on domestic private sector—*line32d* and *FDSAOP*; deposit money banks' assets—as the sum of *line22a* (or *FOSAG* if missing), *line22b* (or *FOSAOG* if missing) and *line22c* (or *FOSAON* if missing), financial system deposits—as the sum of *line24* (or *FOST* if missing) and *line24* (or *FOSD* if missing). The nominal data for Germany for the period prior to the introduction of euro was converted to euro-fixed series (conversion rate = 1.95583).

Real interest rates were computed using their nominal counterparts and GDP deflators. Based on country-specific rates and conditional on data availability, we also computed various spreads: lending/deposit rates, government/corporate yields, short/long maturity. Detailed composition of variables per each country-segment is listed in the tables with estimated factor loadings for each country in Appendix A.[22]

[22] Descriptive statistics and unit root test results (ADF and PP) performed for all series are not included for brevity and are available on request.

5 Empirical results

5.1 Estimated segment-specific financial cycles

Availability of sufficiently long historical data for the financial series represents a rather binding constraint limiting the analysis of some market segments. In order to make use of a richer information content contained also in variables with relatively short history of observations on the one hand, and, on the other—to allow for a possibly longer time span of the estimated financial cycle indicators, which is important for a robust analysis of spillovers and synchronicity—we construct up to four different versions of financial cycles for each market segment and country. Versions v = 1 and v = 2 correspond to, respectively, stationary and non-stationary "long-run" versions of financial cycle measures, i.e. based only on the variables with the longest time span (1960–2015 or the longest period available for a given country-segment). Versions v = 3 and v = 4 correspond to the cycles (stationary and non-stationary, respectively) that are based on the broadest set of relevant variables available in our dataset characterizing that financial segment, which however comes at the expense of a shorter length of the resulting financial cycle estimates.

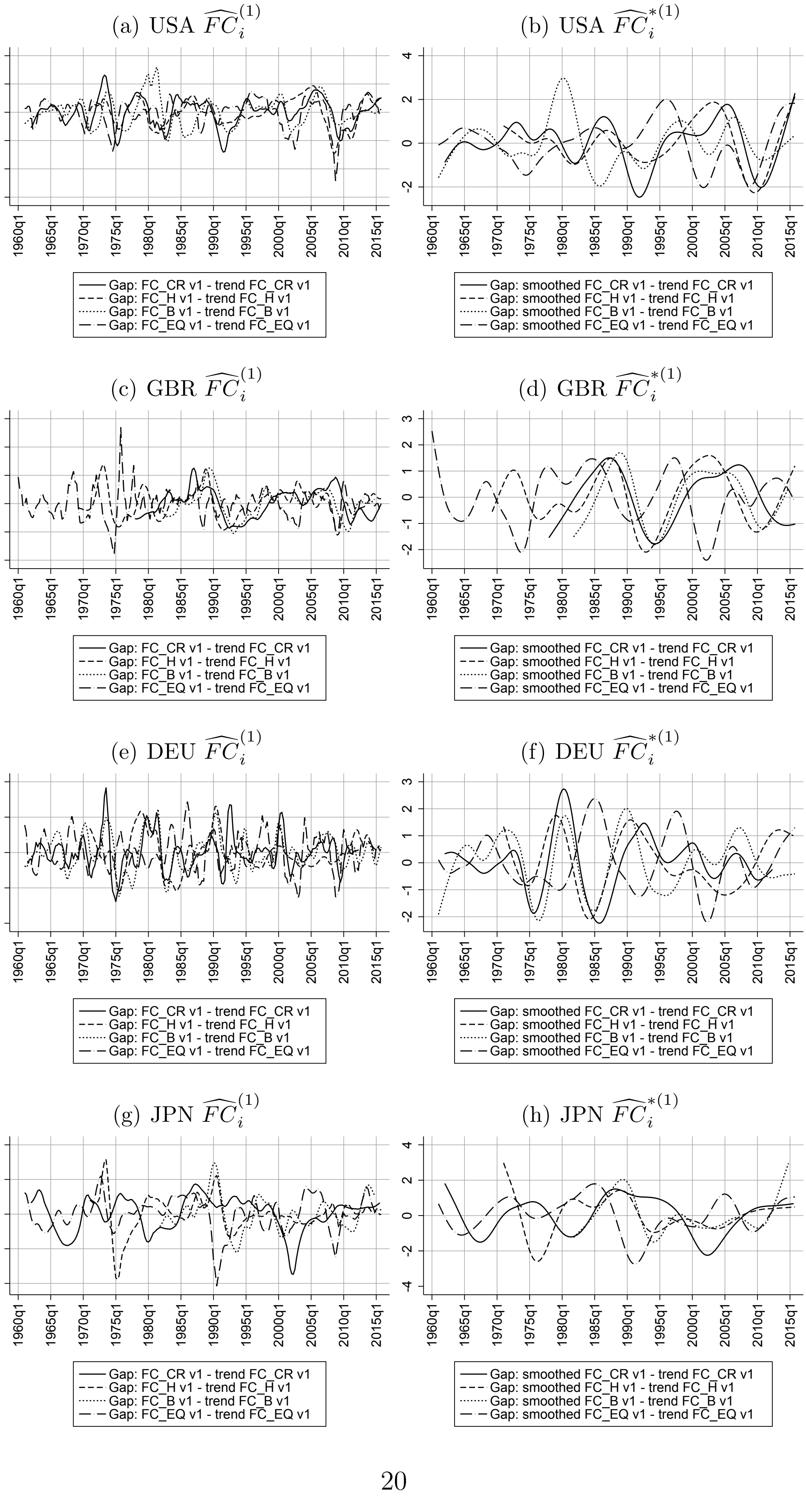
While versions 3 and 4 have a greater information content and hence higher precision, versions 1 and 2 allow to assess evolution of financial cycles over a much longer time horizon. At the same time, the dynamics of financial cycles at lower frequencies and greater amplitudes are rather similar between the short-run and long-run financial cycle versions (e.g. versions 1 and 3, with the exception of the housing cycle, for which version 3 is based on the standardized real housing prices and HP smoothing rather than inclusion of additional variables, due to data constraints–check the factor loadings tables in Appendix A for precise variable compositions). Therefore, for the purposes of the analysis of broad long-run cyclical movements and regularities at lower frequencies we focus on version v = 1 ("stationary long-run" version) as the benchmark financial cycle index for a given country-segment and use it in the spillover and synchronization estimations, as well as to build aggregate financial cycle indicators described in the next sections.

All estimated financial cycles are shown in the Appendix figures, grouped for the ease of navigation by country in the following order: USA, GBR, DEU, JPN; and then, within each country section, arranged by market segment: CR, H, B, EQ, AG.

Importantly, the derived financial cycle indicators do not have a comparable measurement scale and can be interpreted only in terms of the direction of movements, duration of phases and cycles, turning points and relative magnitudes only in the country-segment specific context. Yet, the extent of imbalances can be inferred from the analysis of the cycles expressed in terms of their standard deviations from the sample mean. Therefore, the standardized versions of the benchmark cycles and their HP-smoothed counterparts

Figure 1: Segment-specific benchmark financial cycles, standardized

Note: The figure shows estimated segment-specific benchmark financial cycles $\widehat{FC}_i^{(1)}$ and their medium-run smoothed counterparts $\widehat{FC}_i^{*(1)}$ ($i = CR, H, B, EQ$), standardized and expressed as deviations from the long-run trend. Other versions of the financial cycles are reported in the Appendix.



are also shown in Figure 1. Along these lines, for instance, an increase of the standardized credit financial cycle index above unity would imply loosening of financial conditions by one standard deviation relative to the historical average of that country.

The input variable composition of each financial cycle index, along with the transformations applied, estimated factor loadings and autoregressive parameters, are listed in the Appendix Tables 3, 4, 5, 6, in the same order as figures. In all cases we make every effort to arrive at a balanced mix of signal variables to ensure whenever possible inclusion of variables conveying *"Price–Quantity–Risk"* attributes of the financial markets, which we believe may best capture the build-up of financial imbalances and the following market corrections. The signs of the estimated factor loadings is generally consistent with the economic intuition behind such grouping.[23] In particular, risk and volatility measures tend to bear a negative sign, whereas absolute and relative price and quantity measures load positively, i.e. contraction of market activity is associated with an increase in market volatility, whereas the build-up of financial imbalances during expansions is accompanied by a decline in the perceived risk as conveyed by spreads and acceleration of asset prices and volume of market activity.

Overall, cyclical movements in all financial markets appear to be very pronounced and recurring throughout the analyzed period. The estimated autoregressive parameter characterizing persistence of financial cycles is generally high (for stationary versions of financial cycles—above 0.7 and in many cases above 0.9, signifying almost a random-walk process), which supports the conjecture about the self-reinforcing nature of financial cycles and the build-up of financial imbalances being a very persistent process. In many cases financial cycles also tend to exhibit a slightly asymmetric sawtooth shape with a gradual build-up of financial imbalances followed by a much faster correction with overshooting below the long-run trend level.

Non-stationary versions of financial cycles allow to assess the evolution of the long-run equilibrium trends, which *a priori* are expected to be time-varying and reflect long-run structural transformations in financial markets—something not picked up by strictly stationary financial cycles centered around zero mean. As can be seen from the figures, the detrended versions of non-stationary cycles (i.e. gaps, $\widehat{FC}_i^{(v)}$) are rather similar in terms of dynamics to their stationary counterparts, pointing at a general robustness of the estimates and mutual consistency across estimated cycle versions.

5.2 Analysis of turning points and phases

The BBQ turning point identification routine described in the methodology section is applied to detrended financial cycle indicators and to their HP-smoothed counterparts

[23] Variables with very low values of factor loadings are also reported in the tables for information, but for the purposes of sign and magnitude interpretation should be ignored given their insignificance.

(segment-specific and aggregate). The results are reported in Appendix Tables 7–10 for the USA, GBR, DEU and JPN, respectively. As smoothed financial cycles exhibit much slower adjustment dynamics and less volatility, the procedure naturally yields a lower count of turning points. In addition, smoothing via the HP filter has a tendency to produce symmetric phases by construction, while the raw financial cycles measures appear to be asymmetric in some cases as noted above, which may also introduce distortions to the turning point dates. Nevertheless, the results for the smoothed cycles are generally consistent with those for the raw financial cycles.

When comparing the identified turning points of stationary and non-stationary versions of financial cycles, one should also keep in mind the differences in terms of the nature of the turning points and phases picked up by each version. In particular, stationary cycles by construction tend to include year-on-year differenced variables in the respective dynamic factor models, whereas non-stationary cycles—variables in levels. Therefore, the turning points in the case of stationary financial cycles ($v = 1, 3$) tend to reflect a switch between acceleration and deceleration periods of the level variables. In the case of non-stationary cycles ($v = 2, 4$), the turning points pick up the regime change in the growth rate of the level variables (from positive to negative or vice versa), which roughly corresponds to the crossing of the horizontal axis (from positive to negative values and vice versa) by its detrended stationary cycle counterpart.

Notably, the average duration of phases appears to be rather similar across financial segments and countries. Estimated financial cycles, segment-specific and aggregate alike, tend to have an average phase duration (time between adjacent turning points) of 5 years and an average cycle (peak-to-peak and trough-to-trough) duration of 11 years, based on the smoothed cycles. Unsmoothed financial cycles have a somewhat higher periodicity: 4 and 7 years for phase and cycle duration, respectively, as the BBQ algorithm also picks up transitory shocks specific to a financial segment due to the minimal threshold constraints imposed on the procedure.[24]

As regards country-specific episodes of financial distress, the estimated financial cycles do capture those rather well. In the case of **the USA** (Appendix Figures 4 - 8), financial cycle indexes and associated turning points correctly identify the key asset bubble boom-bust episodes and periods of protracted bear markets, including the bear market in stock markets from 12/1961–06/1962 (Cuban Missile Crisis); 11/1968–05/1970 (post-Nixon election); 11/1980–08/1982 (the Fed interest rate hike and stagflation); 08/1987–12/1987 (Black Monday); 03/2000 (Dot-com bubble); 09/2001–10/2002 (September 11 attacks followed by a bear market); 10/2007–03/2009 (Lehman Brothers and the Great Recession).

[24] Other thresholds were also tested. However only the results for the case with the least constraints are reported here for brevity, as in combination with the turning point identification exercise performed on the smoothed cycles, it should yield sufficient evidence.

The evolution of segment-specific and aggregate financial cycles as estimated in the study suggest that the US economy may be running an elevated risk of a downward correction across its financial segments already in the near future (as of 2018, 1–3 years) if financial activity continues to expand further and fuel asset bubbles. More specifically, although the US monetary policy started to tighten at the end of 2015, the monetary conditions yet have actually been rather easy and credit expanded, whereas stock prices have been following mostly an increasing trend, housing market gained momentum and bond spreads narrowed. These developments are picked up by the expansion of respective financial cycles as documented in the paper up to 2015 (similar tendencies have been prevailing ever since). Notably, the bond market has been following a generally rising trajectory for a rather long time—since the 1980s—as reflected by the downward *long-run trend* dynamics of the US bond financial cycles, reflecting persistently declining yields.

Interesting developments as indicated by the estimated financial cycles can also be observed in the other three countries examined. In **the UK**, major financial market distress episodes include 09/1992 (Black Wednesday, withdrawal of the British pound from the European Exchange Rate Mechanism) and 10/2007–03/2009 (the Great Recession). While the aggregate financial cycle shows that the financial markets overall have achieved sustainable levels after the sharp late-2000s correction, the UK housing market appears to have entered a bubble risk zone in the recent years (Appendix Figure 12). The UK housing market, traditionally expensive with limited supply of property and strong institutions supporting ownership rights, has been globally viewed as a safe haven in the aftermath of the 2008 financial crisis. Although the Bank of England has already tightened regulations on mortgage loans the housing market still demonstrates signs of overheating.

Quite similar tendencies could be discovered in the case of **Germany**. As in the UK, housing prices have been increasing steadily in Germany after the 2008 financial crisis as investors possibly also viewed its property market as an island of stability, while mortgage interest rates were falling, thereby fueling demand to the levels by far exceeding supply growth capacity (Appendix Figure 19). This contrasts sharply with the downward dynamics of the housing and credit financial cycles in the country prior to the crisis.

Finally, the case of **Japan** is also notable for a number of reasons. Japan was viewed as a successful economy prior to the 1980s, able to recover quickly from the post-war crisis and enjoying growth accelerations among the highest in the world back then. Euphoria about development prospects along with financial market deregulation and loose monetary policy undertaken in the late-1970s and the 1980s resulted in the formation of a speculative bubble in the stock market in a low-interest environment and ample liquidity (Appendix Figures 26 - 29). Continuous growth of stock market prices resulted in yet more enthusiasm as corporations reported ever-increasing earnings. In response to escalating asset prices the monetary authority acted by raising interest rates, and in the early 1990s the economic bubble collapsed contributing to the lasting economic stagnation dubbed the "Lost Decade".

When interpreting the dynamics, it should be noted that not all fluctuations in the estimated financial cycle indicators are necessarily associated with financial crisis episodes as their magnitudes differ. In this regard, the smoothed cycles are more instrumental in pinpointing episodes of major distress, although due to additional filtering the turning point algorithm further loses precision and the identified peak and trough dates may not necessarily correspond to real crisis dates. In addition, in some cases the duration of phases may deviate significantly from the average, e.g. the Great Moderation period manifests as an especially long expansion phase with minor transitory shocks in the credit cycles of the USA and the UK.

Table 1: Average phase and cycle duration of financial cycles, years

Note: The table shows average duration of phases (time between alternating turning points) and cycles (peak-peak and trough-trough time) of the benchmark segment-specific and aggregate financial cycles $FC_i^{(1)}$ and their medium-run smoothed counterparts $\widehat{FC}_i^{*(1)}$. Detailed review of turning points and phase/cycle duration can be found in the Appendix.

	USA				GBR				DEU			
	$\boldsymbol{FC}$		$\widehat{\boldsymbol{FC}}^*$		$\boldsymbol{FC}$		$\widehat{\boldsymbol{FC}}^*$		$\boldsymbol{FC}$		$\widehat{\boldsymbol{FC}}^*$	
	τ_{phase}	τ_{cycle}	τ_{phase}	τ_{cycle}	τ_{phase}	τ_{cycle}	τ_{phase}	τ_{cycle}	τ_{phase}	τ_{cycle}	τ_{phase}	τ_{cycle}
CR	3	7	4	8	4	9	10	20	3	5	4	9
H	5	11	6	12	4	8	5	11	4	8	5	10
B	3	7	4	8	4	8	4	8	3	6	4	9
EQ	3	6	6	12	3	6	4	9	3	6	5	9
AG	4	8	4	9	4	9	8	16	4	9	4	9

	JPN				Average			
	$\boldsymbol{FC}$		$\widehat{\boldsymbol{FC}}^*$		$\boldsymbol{FC}$		$\widehat{\boldsymbol{FC}}^*$	
	τ_{phase}	τ_{cycle}	τ_{phase}	τ_{cycle}	τ_{phase}	τ_{cycle}	τ_{phase}	τ_{cycle}
CR	4	8	9	16	**4**	**7**	**7**	**13**
H	4	8	5	9	**4**	**9**	**5**	**10**
B	3	6	4	8	**3**	**7**	**4**	**8**
EQ	3	6	6	11	**3**	**6**	**5**	**10**
AG	4	9	4	9	**4**	**9**	**5**	**11**

5.3 Synchronicity, spillovers and Granger causality

A priori, the behavior of financial markets during economic crisis periods is straightforward as a general slowdown of economic activity leads to declining investment and credit activity accompanied by downward pressures in asset markets. During economic expansions, however, the relationship between financial market segments is more complex. Economic booms and optimistic expectations about future growth facilitate activity across all financial segments (yet, economic expansion is also associated with consumption growth and rising inflation, which reflects negatively on the value of fixed-income instruments), while the growth and development of capital markets on the one hand and the banking sector on the other are argued to be complementary and mutually beneficial. An alternative narrative suggests that asset markets and banks could rather be substitutes, competing for capital as investors consider financing options in the context of trade-offs in terms of the optimal debt-versus-equity balance sheet structure, forms of debt (debt securities versus bank credit). In general, corporations and households may view banks and capital markets as alternative avenues for both borrowing and saving, while in deep and well-diversified capital markets both bond and stock segments may offer similar risk–expected return portfolios. Besides this, segments are also interrelated in terms of interest rates and prices, e.g. the bond market rates serve as a reference for mortgage rates.

Empirical results based on correlations and concordance indicators (Appendix Tables 11–14) also portray a rather mixed picture as synchronization of segment-specific cycles differs much across the four countries examined. The bilateral phase concordance index CI, measuring the fraction of time over which the two financial cycle indexes are in the same phase (expansion or contraction, as defined in the methodology section), shows a particularly high co-movement in the USA between the credit cycles and the other three cycles—housing, debt securities and equity cycles: in all cases the CI values are around 0.6. This result is also supported by fairly high correlation index values. This implies that credit expansion beyond long-run equilibrium levels is systematically associated with the rise of equity and property price levels and lower bond yields (the bond market cycle by construction is moving in the direction of reference bond yields).

There is fairly high phase concordance between the credit cycle and housing and bond market cycles in the case of the UK (CI about 0.6), but not relative to the equity cycle. In general, equity cycles appear to have low co-movement with other segments in all four countries, except for the credit cycle of the USA.

Contemporaneous relationship between the credit cycle and capital market cycles is however less pronounced in the other two countries—Germany and Japan. A notable exception is a particularly high synchronicity between the credit cycle and the bond market cycle in Germany ($CI = 0.76$), which could be indicative of the prominent role of German government bonds, also holding the status of Europe's benchmark bonds, in domestic credit market activity given that corporate debt securities market has been rather shallow in Germany. Another notable outlier is a rather high correlation between the debt securities and the housing cycles in Japan (correlation = 0.7), likely signifying close linkages between government bond yields and mortgages in a cyclical context, albeit this result is not supported by the insignificant value of the CI index.

To complement synchronicity analysis we next examine dynamic interactions between segment-specific cycles by means of unrestricted stationary VAR models involving the benchmark financial cycles $FC_i^{(1)}$ taken in gaps (deviations from time-varying trends, standardized) and first differences (standardized) for each country in the sample.[25] The

[25] Extraction of financial cycles via a dynamic factor model is particularly well-suited to the analysis of spillovers between financial market segments as the resulting shrinkage of data allows to estimate

latter exercise is performed for robustness as the estimated autoregressive coefficient in many cases is rather close to unity, although the benchmark versions of financial cycles formally pass unit-root tests.

Table 2: Granger causality test results

Note: The table shows the results of pairwise and joint ("ALL") Granger causality tests for benchmark (v=1) financial cycles. Dependent variables (d.v.) are listed in the first column, independent variables are listed in the first row for each country. 1, 5, 10 indicate statistical significance at the respective level of significance; "-" indicates the variable is not found to Granger cause the dependent variable. (gap) denotes a VAR model in deviations from the trend; (diff) denotes a VAR model in first-differences. IRF plots of the associated models are in the Appendix.

USA

	(gap)	FC_{CR}	FC_H	FC_B	FC_{EQ}	ALL
d.v.	FC_{CR}		1	1	1	1
d.v.	FC_H	-		5	-	5
d.v.	FC_B	-	5		5	1
d.v.	FC_{EQ}	-	5	-		10

	(diff)	FC_{CR}	FC_H	FC_B	FC_{EQ}	ALL
d.v.	FC_{CR}		5	5	10	1
d.v.	FC_H	5		1	-	1
d.v.	FC_B	5	-		-	5
d.v.	FC_{EQ}	-	1	-		-

GBR

	(gap)	FC_{CR}	FC_H	FC_B	FC_{EQ}	ALL
d.v.	FC_{CR}		-	-	-	10
d.v.	FC_H	-		5	5	5
d.v.	FC_B	5	1		1	1
d.v.	FC_{EQ}	-	-	-		-

	(diff)	FC_{CR}	FC_H	FC_B	FC_{EQ}	ALL
d.v.	FC_{CR}		-	5	-	10
d.v.	FC_H	-		5	1	1
d.v.	FC_B	5	-		-	5
d.v.	FC_{EQ}	-	-	-		-

DEU

	(gap)	FC_{CR}	FC_H	FC_B	FC_{EQ}	ALL
d.v.	FC_{CR}		5	5	5	1
d.v.	FC_H	-		5	-	-
d.v.	FC_B	-	1		5	1
d.v.	FC_{EQ}	-	-	-		10

	(diff)	FC_{CR}	FC_H	FC_B	FC_{EQ}	ALL
d.v.	FC_{CR}		1	5	1	1
d.v.	FC_H	10		5	-	-
d.v.	FC_B	-	1		-	1
d.v.	FC_{EQ}	10	10	-		5

JPN

	(gap)	FC_{CR}	FC_H	FC_B	FC_{EQ}	ALL
d.v.	FC_{CR}		-	-	-	-
d.v.	FC_H	-		5	-	5
d.v.	FC_B	-	10		1	1
d.v.	FC_{EQ}	1	-	5		1

	(diff)	FC_{CR}	FC_H	FC_B	FC_{EQ}	ALL
d.v.	FC_{CR}		-	-	-	-
d.v.	FC_H	-		5	-	-
d.v.	FC_B	-	10		10	-
d.v.	FC_{EQ}	-	-	-		10

Identification of shocks in VAR models is based on Cholesky decomposition with the following variable ordering: FC_{CR}, FC_H, FC_B, FC_{EQ}. As discussed in greater detail in the methodology section, the triangular identification structure imposed by such ordering implies that, for instance, the credit cycle reacts only with a lag to the shocks in the housing cycle, while the response of the debt securities cycle to shocks in the housing market can be contemporaneous (within the same quarter).

Estimation of spillover effects yields results consistent with the co-movement analysis (see the IRF plots in the Appendix Figures 10, 17, 24, 31 for the USA, GBR, DEU and JPN, respectively, and Granger causality results in Table 2). Much stronger Granger-causal relationship is found among segment-specific cycles in the case of the USA. In particular, estimation results point at a significant impact on the credit market cycles of shocks originating in other financial segments, with the peak effect reached within 6

a low-dimensional VAR while still taking advantage of information content contained in a larger dataset, especially owing to the fact that the "curse of dimensionality" is often further exacerbated by a generally short length of the series in macroeconomic applications.

quarters. This is indicative of the importance of the wealth channel in nominal shock transmissions also from the perspective of the accumulation of imbalances as evidenced by financial cycles.

Similar significant spillover effects on the credit cycle from other financial cycles is found in the case of Germany, but not Japan and the UK. Notably, the relationship in the other direction, i.e. the impact of credit cycles on other segment-specific cycles is not statistically significant across all countries, with the exception of the bond market of the UK and possibly the housing and the bond markets of the USA (significant at the 5% level only for the VAR based on first-differenced financial cycle measures).

Equity market cycles appear to be decoupled from other financial cycles in terms of response to shocks stemming from the latter, except for the impact of housing cycles on equity market in the USA. In Germany, statistically significant Granger causality in both directions is found between the housing and the bond market financial cycles. For all four countries the results suggest the bond market cycle may Granger cause the housing cycle. The latter is the only significant and robust relationship identified in the case of Japan, besides a marginally significant impact on the bond cycle of the housing and the equity cycles.

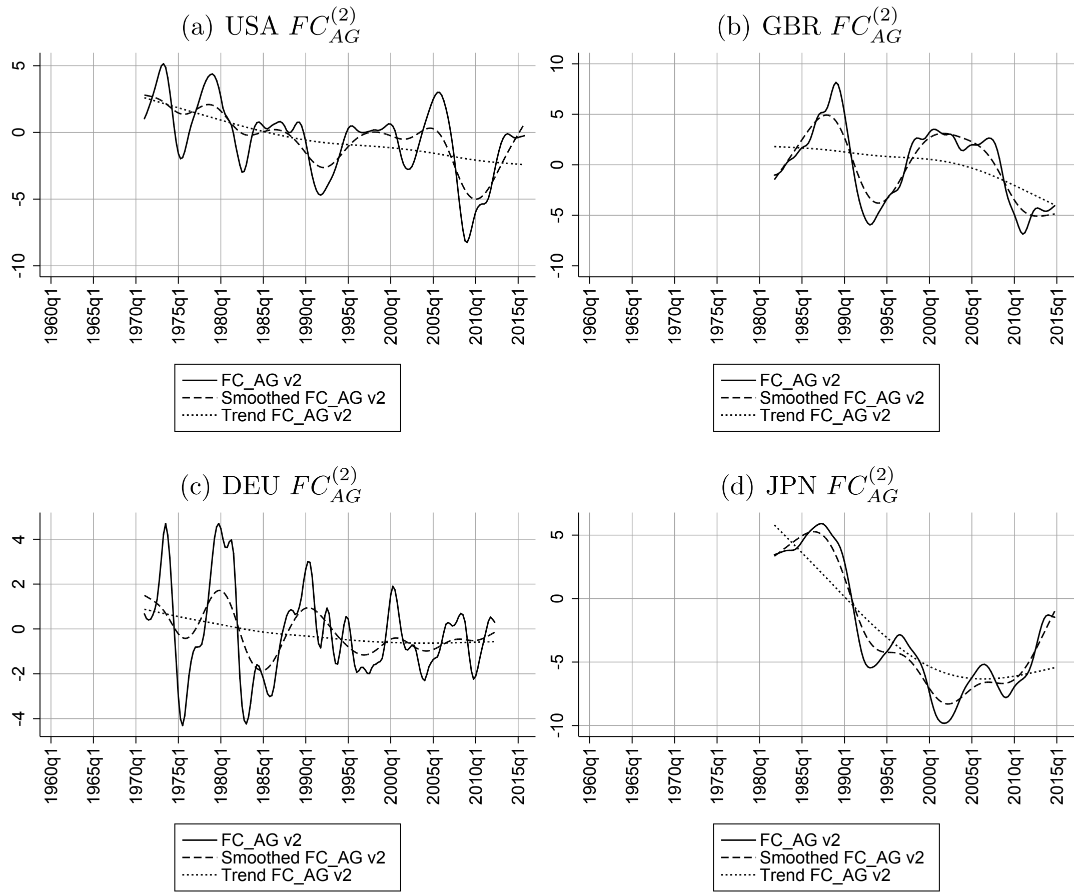
Summarizing the co-movement and the spillover analysis, the results suggest that spillovers between segment-specific cycles are significant and therefore deep capital markets and mutually integrated financial market segments are prone to the risks of simultaneous distress and mutually reinforcing spillovers. This somewhat weakens the argument that diversification of financial markets may necessarily bring greater systemic stability, as well as underscores the importance of an overarching approach to monitoring and addressing segment-specific imbalances, mitigating spillovers and resulting reciprocal amplification of shocks, which could initially be of relatively minor magnitudes. At the same time, the analysis does not yield robust evidence on the differences between the market-based (the USA and the UK) and the bank-based systems (Germany and Japan), and all results are rather country-specific with a few common regularities across all countries in the sample.

5.4 Aggregate financial cycles

As a final exercise, we estimate aggregate financial cycles that summarize common dynamics across all financial market segments of a given country (Appendix Figures 8, 15, 22, 29). Aggregate financial cycles $FC_{AG}^{(v)}$ are derived via the Kalman filter using two approaches: version v=1, similarly to the segment-specific cycles, is estimated using a dynamic factor model incorporating standardized and transformed financial series pooled across all four market segments (the included variables are identical to those included in the benchmark v=1 versions of segment-specific cycles; see the variable compositions

Figure 2: Aggregate financial cycles

Note: The figure shows aggregate financial cycles $FC_{AG}^{(2)}$, its HP-smoothed version and trend. $FC_{AG}^{(1)}$ is reported in the Appendix.



in the Appendix Tables 3–6); version v=2 is obtained by extracting common variation from the four estimated segment-specific benchmark financial cycles $FC_{CR}^{(1)}$, $FC_{H}^{(1)}$, $FC_{B}^{(1)}$, $FC_{EQ}^{(1)}$.

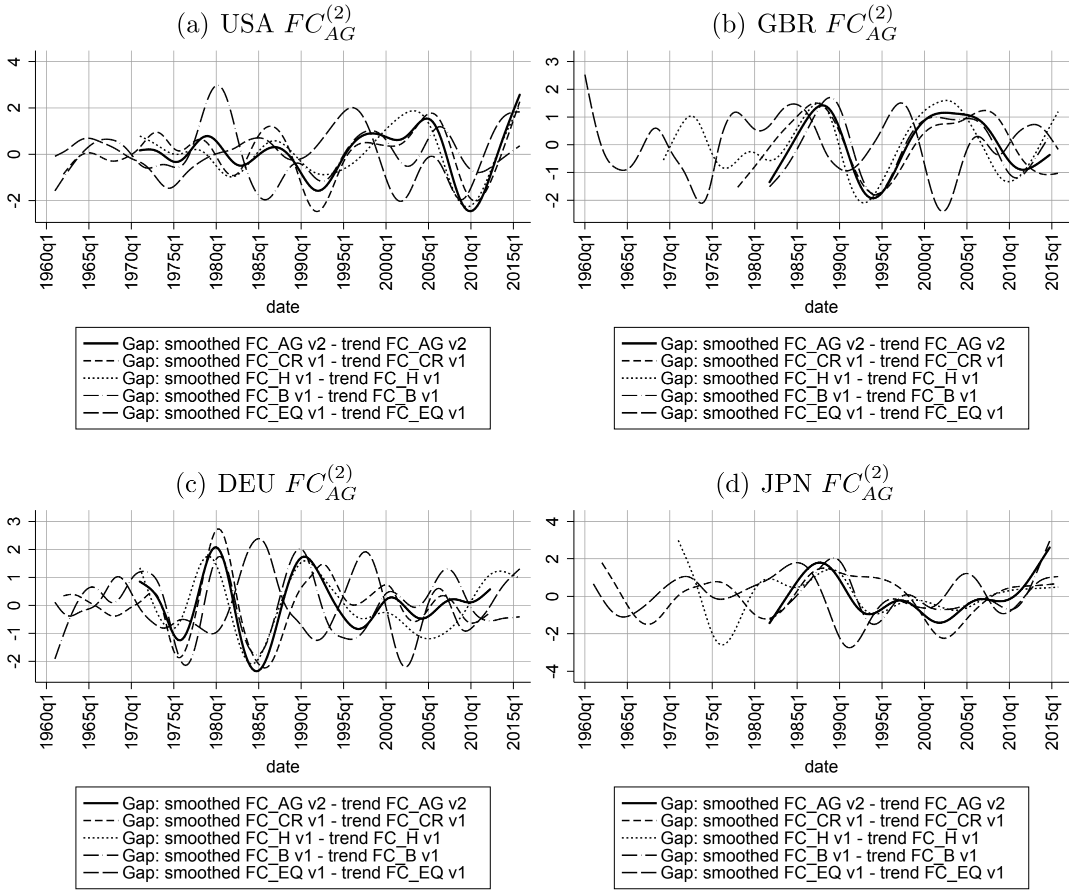
The latter version, $FC_{AG}^{(2)}$ (also shown in Figure 2, in addition to the Appendix figures), is the preferred indicator as by construction it treats each financial segment symmetrically[26] and does not over-represent a particular financial segment for which more variables are available over the sample period: $FC_{AG}^{(1)}$ generally includes more credit market variables. Nevertheless, de facto this does not matter much as the estimates obtained using the two approaches yield almost identical results as can be seen in subfigure (e) of Appendix Figures 8, 15, 22, 29.

Overall, estimated aggregate financial cycles do a decent job summarizing the common component across the different market segments, as could be judged from the scatterplots

[26] This however does not imply that each of the four financial segments plays an equal role in the economy. Alternative weighting schemes could be applied based on the relative size of the financial segment in the economy, or proportional to their contribution to explaining real economic growth dynamics. The objective of our exercise here is merely to extract common variation.

Figure 3: Aggregate and segment financial cycles (detrended and smoothed)

Note: The figure shows HP-smoothed detrended aggregate financial cycles $FC_{AG}^{(2)}$ and benchmark segment-specific cycles.



(Figures 9, 16, 23, 30) and correlation/concordance metrics (Tables 11–14). The only exception is the equity cycle, which tends to be correlated and load marginally better on the aggregate cycle only in the case of the USA (although the relationship is still fuzzy), also suggesting that equity markets tend to decouple from other financial segments with a greater role played by idiosyncratic factors.

All major financial distress episodes are captured well by aggregate cycles. The turning points analysis yields results generally consistent with the segment-specific cycles (Appendix Tables 7–10) with an average phase duration of 4-5 years and peak-to-peak and trough-to-trough cycle duration of 9-11 years (Table 1).

6 Policy implications

As a result of the Great Recession the role of financial markets as a source of macroeconomic instability has received an increasing attention from policy-makers and certain aspects of the growth-finance nexus are being revisited in applied contexts also. In particular, the established approach in macroeconomics that allowed typically only for a limited role of the financial sector in the business cycle fluctuations in form of frictions and focusing solely on consumer prices (as opposed to asset prices and credit marlet developments) as the price indicator of an overheating economy has proved to be limited.

Our paper offers additional empirical evidence supporting the view that financial markets are prone to persistent cyclical movements with rather regular phases and relatively long duration of cycles—about 10 years on average. The results of the study thus are most closely related to the line of reasoning of the Bank for International Settlements (BIS (2014, 2015), Borio (2013, 2014), Borio et al. (2013, 2014)) vouching for a more pro-active use of monetary policy and macroprudential policy tools along with forward guidance to address inherent procyclicality of financial markets, reduce systemic vulnerabilities associated with the financial system, and incorporate financial variables into output gap estimation methodology. This implies high relevance of more subtle policy instruments and regulations focusing on specific financial segments in addition to conventional interest rate policy measures that are broad-based, affecting all market segments.

In light of the revealed importance of financial cycles for economic growth as highlighed by the recent global crisis, policy-makers should more closely monitor unsustainable developments across all financial market segments, including emerging quasi financial institutions and market niches. In this regard, the present study offers an empirical approach to measure financial imbalances in a compact yet structured way, that is, separately by financial market segment (since segment-specific cycles exhibit different dynamic patterns and do not necessarily co-move) and by taking advantage of relevant information in a wide range of variables that have high signaling content as far as the boom-bust developments in financial markets is concerned—price/return, quantity/activity, risk/volatility. The latter also calls for additional efforts needed to generate quality data at least at quarterly frequencies for each of the potentially fragile segments to enable continuous monitoring of potential bubbles and enable timely policy action, as data availability is often not satisfactory. The estimation method employed in the study could be useful for monitoring financial imbalances in real time as the Kalman filter/smoother can effectively handle the "jagged edge" data issues (new observations may become available only with a lag for some variables used in the construction of financial cycles) and allows to model relationships in a more complex state-space structure if needed.

Related to the above, the importance of timely policy interventions cannot be overstated. Not only this is important in light of the drastic macroeconomic effects that financial cycle contractions may lead to, but also because of the risks associated with inappropriate late response, after the bubble has already burst, which could be even more harmful being procyclical and contributing to the problems created by the financial cycle downturn. [27]

Another important aspect that needs to be understood better and addressed by policymakers is the interconnectedness of financial segments and spillovers between them, which are found across all countries we examine, but are likely to be of greater economic significance in deep capital market systems as opposed to systems relying on traditional forms of financial intermediation. Diversification of financial markets is certainly desirable and has been a particularly important policy theme recently in the EU in light of its generally high reliance on the banking system which exacerbated the crisis and gave additional impetus to the Capital Markets Union initiative to strengthen Europe's financial system. At the same time, it appears that deep capital markets also are prone to the risks of their own associated with mutual spillovers and co-movement between individual market segments, which may amplify their overall macroeconomic impact during major distress periods. Therefore, the exact transmission mechanisms between financial market segments need to be analyzed further and taken into account in the design of a more resilient future financial system.

7 Conclusion

There are still many gray areas in our understanding of the role the financial sector plays in economic growth and development, which likely extends far beyond being a passive accelerator of real shocks. The cyclical nature of financial activity with persistent and recurring build-up of imbalances followed by sharp contractions has important direct implications for sustainability of economic growth.

The paper contributes to the debate by providing additional empirical evidence and analysis of financial cycles at the level of individual financial segments, as well as at the national level, for the four systemically important countries with developed financial systems. Strong cyclical patterns are revealed in each financial segment, and, in light of severe macroeconomic consequences that contraction of financial cycles may have, it is important to embark on research on the nature of these cycles and the driving forces behind. Further empirical work is also needed to uncover the transmission mechanisms behind financial market activity fluctuations, to investigate the implications of different financial cycles for macroeconomic stability, including interactions between financial cycles and external and internal macroeconomic imbalances, analysis of cross-country

[27] In this respect, Brunnermeier and Schnabel (2014) provide a useful review of asset bubbles over the past 400 years along with policy responses. Among other episodes, Australian real estate bubble and the role of the Reserve Bank of Australia in defusing it at the early stages without substantial interest rate increases is noted as an example of a successful intervention. This contrasts with the interest rate hike by the Fed in 2004, which was not sufficient to curb the US subprime mortgage bubble. The study also showcases a negative experience of the Swedish central bank raising interest rates in 2010 in attempt to limit lending and prevent the real estate bubble, which however resulted in disinflation and depressed economic growth.

financial cycle spillovers.

This will allow to enhance our understanding of the policies needed and develop appropriate instruments and regulations to continuously monitor imbalances, defuse the bubbles in a timely manner or minimize the negative impact of financial shocks. Finally, more effort is needed to arrive at better measures of output gaps that take into account accumulation of imbalances in financial markets, as well as a theoretical framework that relates savings and investments dynamics to the build-up of financial imbalances and recurring financial cycles in a general equilibrium context. As financial innovation is progressing fast and new financial instruments are engineered, the complexity of financial systems is ever-increasing, which calls for a better understanding of the deep fundamental factors that drive fluctuations across financial markets.

Appendix A: Tables

Table 3: Factor loadings and autoregressive coefficients: USA

Note: The table shows factor loadings (vector B) from the dynamic factor model associated with the corresponding segment-specific or aggregate financial cycles. f_{t-1} denotes the autoregressive coefficient (A) of the latent factor (financial cycle index). **Attr.** indicates the market attribute the variable captures: *(P)rice, (Q)uantity, (R)isk*. **Trans.** reports the transformations applied to the input signal variables: *std*—standardization, Δyoy—year-on-year difference, $std\%\Delta yoy$—year-on-year percent change.

USA $FC_{CR}^{(1)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.93
Private credit by banks, % GDP	Q	$std\Delta yoy$	0.25
Private credit by banks, LCU	Q	$std\%\Delta yoy$	0.32
Lending interest rate, % pa	P	$std\Delta yoy$	0.13
Money market interest rate, % pa	P	$std\Delta yoy$	0.16
Spread between lending interest rate and Federal funds rate	R	*std*	-0.25
Spread between lending interest rate and government bond rate	R	*std*	-0.23

USA $FC_{CR}^{(2)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.99
Private credit by banks, % GDP	Q	*std*	0.01
Private credit by banks, LCU	Q	*std*	0.10
Lending interest rate, % pa	P	*std*	0.02
Money market interest rate, % pa	P	*std*	-0.02
Spread between lending interest rate and Federal funds rate	R	*std*	0.08
Spread between lending interest rate and government bond rate	R	*std*	0.09

USA $FC_{CR}^{(3)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.96
Private credit by banks, % GDP	Q	$std\Delta yoy$	0.23
Financial system deposits, % GDP	Q	$std\Delta yoy$	0.07
Deposit money banks' assets, % GDP	Q	$std\Delta yoy$	0.20
Private credit by banks, LCU	Q	$std\%\Delta yoy$	0.26
Financial system deposits, LCU	Q	$std\%\Delta yoy$	0.20
Deposit money banks' assets, LCU	Q	$std\%\Delta yoy$	0.26
Lending interest rate, % pa	P	$std\Delta yoy$	0.06
Money market interest rate, % pa	P	$std\Delta yoy$	0.08
Spread between lending interest rate and government bond rate	R	*std*	-0.11
Spread between lending interest rate and Federal funds rate	R	*std*	-0.14
Bank credit to bank deposits (%)	Q	$std\Delta yoy$	0.16
Total credit to Households & NPISHs, % of GDP	Q	$std\Delta yoy$	0.13
Total credit to Households & NPISHs, LCU	Q	$std\%\Delta yoy$	0.22
Total credit to NFCs, % of GDP	Q	$std\Delta yoy$	0.17
Total credit to NFCs, LCU	Q	$std\%\Delta yoy$	0.24
Monetary Base, LCU	Q	$std\%\Delta yoy$	-0.11
Ratio of Monetary Base to Broad Money, %	Q	$std\Delta yoy$	-0.17
M2	Q	$std\%\Delta yoy$	0.12
M1	Q	$std\%\Delta yoy$	-0.10
Broad Money Liabilities, LCU	Q	$std\%\Delta yoy$	-0.01

USA $FC_{CR}^{(4)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			1.01
Private credit by banks, % GDP	Q	*std*	0.00
Financial system deposits, % GDP	Q	*std*	0.03
Deposit money banks' assets, % GDP	Q	*std*	-0.02
Private credit by banks, LCU	Q	*std*	0.05
Financial system deposits, LCU	Q	*std*	0.05
Deposit money banks' assets, LCU	Q	*std*	0.05
Lending interest rate, % pa	P	*std*	-0.01
Money market interest rate, % pa	P	*std*	-0.02
Spread between lending interest rate and government bond rate	R	*std*	0.03
Spread between lending interest rate and Federal funds rate	R	*std*	0.03
Bank credit to bank deposits (%)	Q	*std*	-0.03
Total credit to Households & NPISHs, % of GDP	Q	*std*	0.05
Total credit to Households & NPISHs, LCU	Q	*std*	0.05

Total credit to NFCs, % of GDP	Q	*std*	0.04
Total credit to NFCs, LCU	Q	*std*	0.05
Monetary Base, LCU	Q	*std*	0.04
Ratio of Monetary Base to Broad Money, %	Q	*std*	0.02
M2	Q	*std*	0.05
M1	Q	*std*	0.05
Broad Money Liabilities, LCU	Q	*std*	0.05

USA $FC_H^{(1)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.95
Multifamily Residential Mortgages, Assets, LCU	Q	$std\%\Delta yoy$	0.19
Property prices, real, index, 2010 = 100	P	$std\%\Delta yoy$	0.30
Price to rent ratio	P	$std\Delta yoy$	0.28
Price to income ratio	P	$std\Delta yoy$	0.27

USA $FC_H^{(2)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			1.00
Multifamily Residential Mortgages, Assets, LCU	Q	*std*	0.08
Property prices, real, index, 2010 = 100	P	*std*	0.08
Price to rent ratio	P	*std*	0.03
Price to income ratio	P	*std*	-0.05

USA $FC_H^{(3)}$	**Attr.**	**Trans.**	**A/B**
Property prices, real, index, 2010 = 100, standardized	P	*std*	(hp)

USA $FC_B^{(1)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.90
10Y-3M government bond spread	R	*std*	-0.33
Moody's Seasoned Aaa Corporate Bond Yield	P	$std\Delta yoy$	0.29
3-Month Treasury Bill: Secondary Market Rate	P	$std\Delta yoy$	0.30
Aaa-3M government bond spread	R	*std*	-0.31
Nonfinancial corporate business; corporate bonds; liability, Level	Q	$std\%\Delta yoy$	-0.08

USA $FC_B^{(2)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.98
10Y-3M government bond spread	R	*std*	-0.09
Moody's Seasoned Aaa Corporate Bond Yield	P	*std*	0.15
3-Month Treasury Bill: Secondary Market Rate	P	*std*	0.18
Aaa-3M government bond spread	R	*std*	-0.18
Nonfinancial corporate business; corporate bonds; liability, Level	Q	*std*	-0.14

USA $FC_B^{(3)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.98
10Y-3M government bond spread	R	*std*	-0.18
Moody's Seasoned Aaa Corporate Bond Yield	P	$std\Delta yoy$	0.04
3-Month Treasury Bill: Secondary Market Rate	P	$std\Delta yoy$	0.01
Aaa-3M government bond spread	R	*std*	-0.16
Nonfinancial corporate business; corporate bonds; liability, Level	Q	$std\%\Delta yoy$	0.08
Moody's Seasoned Baa Corporate Bond Yield	P	$std\Delta yoy$	0.09
Moody's Seasoned Baa Corp. Bond Yield rel. to Yield on 10Y Treasury	R	*std*	-0.05
Debt securities by all issuers, amt outstanding, mln LCU	Q	$std\%\Delta yoy$	0.16
International debt securities by all issuers, amt outstanding, mln LCU	Q	$std\%\Delta yoy$	0.02
Outstanding domestic private debt securities to GDP (%)	Q	$std\Delta yoy$	0.22
Outstanding domestic public debt securities to GDP (%)	Q	$std\Delta yoy$	-0.24
Outstanding international private debt securities to GDP (%)	Q	$std\Delta yoy$	0.23
Outstanding international public debt securities to GDP (%)	Q	$std\Delta yoy$	0.03

USA $FC_{B}^{(4)}$	Attr.	Trans.	A/B
f_{t-1}			0.99
10Y-3M government bond spread	R	*std*	-0.05
Moody's Seasoned Aaa Corporate Bond Yield	P	*std*	0.07
3-Month Treasury Bill: Secondary Market Rate	P	*std*	0.09
Aaa-3M government bond spread	R	*std*	-0.09
Nonfinancial corporate business; corporate bonds; liability, Level	Q	*std*	-0.10
Moody's Seasoned Baa Corp. Bond Yield rel. to Yield on 10Y Treasury	R	*std*	-0.09
Moody's Seasoned Baa Corporate Bond Yield	P	*std*	-0.03
Outstanding domestic private debt securities to GDP (%)	Q	*std*	-0.12
Outstanding domestic public debt securities to GDP (%)	Q	*std*	-0.03
Outstanding international private debt securities to GDP (%)	Q	*std*	-0.14
Outstanding international public debt securities to GDP (%)	Q	*std*	-0.02
Debt securities by all issuers, amt outstanding, mln LCU	Q	*std*	-0.09
International debt securities by all issuers, amt outstanding, mln LCU	Q	*std*	-0.15

USA $FC_{EQ}^{(1)}$	Attr.	Trans.	A/B
f_{t-1}			0.81
Average stock market index value	P	$std\%\Delta yoy$	0.42
Standard deviation of daily stock market returns, quarterly avg	R	*std*	-0.39
Average stock market index daily return, quarterly avg	P	*std*	0.15

USA $FC_{EQ}^{(2)}$	Attr.	Trans.	A/B
f_{t-1}			1.00
Average stock market index value	P	*std*	0.09
Standard deviation of daily stock market returns, quarterly avg	R	*std*	0.04
Average stock market index daily return, quarterly avg	P	*std*	-0.01

USA $FC_{EQ}^{(3)}$	Attr.	Trans.	A/B
f_{t-1}			0.87
Average stock market index value	P	$std\%\Delta yoy$	0.38
Standard deviation of daily stock market returns, quarterly avg	R	*std*	-0.32
Average stock market index daily return, quarterly avg	P	*std*	0.11
Stock market turnover ratio (%)	Q	$std\Delta yoy$	-0.15
Stock market capitalization to GDP (%)	Q	$std\Delta yoy$	0.40

USA $FC_{EQ}^{(4)}$	Attr.	Trans.	A/B
f_{t-1}			1.00
Average stock market index value	P	*std*	0.11
Standard deviation of daily stock market returns, quarterly avg	R	*std*	0.05
Average stock market index daily return, quarterly avg	P	*std*	-0.01
Stock market turnover ratio (%)	Q	*std*	0.10
Stock market capitalization to GDP (%)	Q	*std*	0.11

USA $FC_{AG}^{(1)}$	Attr.	Trans.	A/B
f_{t-1}			0.92
Average stock market index value	P	$std\%\Delta yoy$	0.03
Standard deviation of daily stock market returns, quarterly avg	R	*std*	-0.14
Average stock market index daily return, quarterly avg	P	*std*	0.00
10Y-3M government bond spread	R	*std*	-0.22
Moody's Seasoned Aaa Corporate Bond Yield	P	$std\Delta yoy$	0.11
3-Month Treasury Bill: Secondary Market Rate	P	$std\Delta yoy$	0.27
Aaa-3M government bond spread	R	*std*	-0.19
Nonfinancial corporate business; corporate bonds; liability, Level	Q	$std\%\Delta yoy$	-0.03
Multifamily Residential Mortgages, Assets, LCU	Q	$std\%\Delta yoy$	0.23
Property prices, real, index, 2010 = 100	P	$std\%\Delta yoy$	0.26
Price to rent ratio	P	$std\Delta yoy$	0.23
Price to income ratio	P	$std\Delta yoy$	0.21
Private credit by banks, % GDP	Q	$std\Delta yoy$	0.26
Private credit by banks, LCU	Q	$std\%\Delta yoy$	0.34
Lending interest rate, % pa	P	$std\Delta yoy$	0.21
Money market interest rate, % pa	P	$std\Delta yoy$	0.22
Spread between lending interest rate and Federal funds rate	R	*std*	-0.19
Spread between lending interest rate and government bond rate	R	*std*	-0.12

USA $FC^{(2)}_{AG}$	Attr.	Trans.	A/B
f_{t-1}			0.94
$FC^{(1)}_{CR}$	C	*std*	0.29
$FC^{(1)}_{H}$	C	*std*	0.23
$FC^{(1)}_{B}$	C	*std*	0.21
$FC^{(1)}_{EQ}$	C	*std*	0.14

Table 4: Factor loadings and autoregressive coefficients: GBR

Note: The table shows factor loadings (vector B) from the dynamic factor model associated with the corresponding segment-specific or aggregate financial cycles. f_{t-1} denotes the autoregressive coefficient (A) of the latent factor (financial cycle index). **Attr.** indicates the market attribute the variable captures: *(P)rice, (Q)uantity, (R)isk.* **Trans.** reports the transformations applied to the input signal variables: *std*—standardization, Δyoy—year-on-year difference, $std\%\Delta yoy$—year-on-year percent change.

GBR $FC_{CR}^{(1)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.95
Total credit to private non-financial sector, % of GDP	Q	$std\Delta yoy$	0.28
Private credit by banks, LCU	Q	$std\%\Delta yoy$	0.23
Lending interest rate, % pa	P	$std\Delta yoy$	0.00
Money market interest rate, % pa	P	$std\Delta yoy$	-0.01
Spread between 3-month and overnight interbank interest rate, pp	R	*std*	0.03
Spread between lending interest rate and treasury bill rate, pp	R	*std*	0.03

GBR $FC_{CR}^{(2)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			1.00
Total credit to private non-financial sector, % of GDP	Q	*std*	0.08
Private credit by banks, LCU	Q	*std*	0.08
Lending interest rate, % pa	P	*std*	-0.02
Money market interest rate, % pa	P	*std*	-0.01
Spread between 3-month and overnight interbank interest rate, pp	R	*std*	0.00
Spread between lending interest rate and treasury bill rate, pp	R	*std*	-0.02

GBR $FC_{CR}^{(3)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.98
Total credit to private non-financial sector, % of GDP	Q	$std\Delta yoy$	0.24
Private credit by banks, LCU	Q	$std\%\Delta yoy$	0.11
Lending interest rate, % pa	P	$std\Delta yoy$	0.00
Money market interest rate, % pa	P	$std\Delta yoy$	0.00
Spread between lending interest rate and treasury bill rate, pp	R	*std*	0.01
Spread between 3-month and overnight interbank interest rate, pp	R	*std*	0.03
Deposit money banks' assets to GDP (%)	Q	$std\Delta yoy$	0.23
Corporate Borrowing Spread on Loans from Banks	R	*std*	-0.11
Total credit to Households & NPISHs, % of GDP	Q	$std\Delta yoy$	0.19
Total credit to Households & NPISHs, LCU	Q	$std\%\Delta yoy$	0.15
Total credit to NFCs, % of GDP	Q	$std\Delta yoy$	0.19
Total credit to NFCs, LCU	Q	$std\%\Delta yoy$	0.18
Monetary Base	Q	$std\%\Delta yoy$	-0.01
Ratio of Monetary Base to Broad Money, %	Q	$std\Delta yoy$	-0.09
M3	Q	$std\%\Delta yoy$	0.18
M1	Q	$std\%\Delta yoy$	0.13

GBR $FC_{CR}^{(4)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			1.01
Total credit to private non-financial sector, % of GDP	Q	*std*	0.06
Private credit by banks, LCU	Q	*std*	0.07
Lending interest rate, % pa	P	*std*	-0.02
Money market interest rate, % pa	P	*std*	-0.01
Spread between lending interest rate and treasury bill rate, pp	R	*std*	-0.01
Spread between 3-month and overnight interbank interest rate, pp	R	*std*	0.00
Deposit money banks' assets to GDP (%)	Q	*std*	0.06
Corporate Borrowing Spread on Loans from Banks	R	*std*	0.02
Total credit to Households & NPISHs, % of GDP	Q	*std*	0.06
Total credit to Households & NPISHs, LCU	Q	*std*	0.06
Total credit to NFCs, % of GDP	Q	*std*	0.05
Total credit to NFCs, LCU	Q	*std*	0.06
Monetary Base	Q	*std*	0.06
Ratio of Monetary Base to Broad Money, %	Q	*std*	-0.02
M3	Q	*std*	-0.02
M1	Q	*std*	0.04

GBR $FC_H^{(1)}$	Attr.	Trans.	A/B
f_{t-1}			0.90
Household Variable Mortgage Rate, % pa	P	$std\Delta yoy$	0.19
Property prices, real, index, 2010 = 100	P	$std\%\Delta yoy$	0.39
Price to rent ratio	P	$std\Delta yoy$	0.38

GBR $FC_H^{(2)}$	Attr.	Trans.	A/B
f_{t-1}			1.00
Household Variable Mortgage Rate, % pa	P	std	-0.08
Property prices, real, index, 2010 = 100	P	std	0.08
Price to rent ratio	P	std	0.08

GBR $FC_H^{(3)}$	Attr.	Trans.	A/B
f_{t-1}			0.91
Household Variable Mortgage Rate, % pa	P	$std\Delta yoy$	0.18
Property prices, real, index, 2010 = 100	P	$std\%\Delta yoy$	0.34
Price to rent ratio	P	$std\Delta yoy$	0.40
Price to income ratio	P	$std\Delta yoy$	0.38

GBR $FC_H^{(4)}$	Attr.	Trans.	A/B
f_{t-1}			1.01
Household Variable Mortgage Rate, % pa	P	std	-0.08
Property prices, real, index, 2010 = 100	P	std	0.10
Price to rent ratio	P	std	0.11
Price to income ratio	P	std	0.09

GBR $FC_B^{(1)}$	Attr.	Trans.	A/B
f_{t-1}			0.92
Treasury Bill Rate, % pa	P	$std\Delta yoy$	0.14
10Y-3M government bond spread, pp	R	std	-0.32
Outstanding international public debt securities to GDP (%)	Q	$std\Delta yoy$	-0.20
Outstanding international private debt securities to GDP (%)	Q	$std\Delta yoy$	0.02

GBR $FC_B^{(2)}$	Attr.	Trans.	A/B
f_{t-1}			0.99
10Y-3M government bond spread, pp	R	std	-0.12
Treasury Bill Rate, % pa	P	std	0.18
Outstanding international public debt securities to GDP (%)	Q	std	-0.09
Outstanding international private debt securities to GDP (%)	Q	std	-0.16

GBR $FC_B^{(3)}$	Attr.	Trans.	A/B
f_{t-1}			0.95
Treasury Bill Rate, % pa	P	$std\Delta yoy$	0.06
10Y-3M government bond spread, pp	R	std	-0.21
Outstanding domestic private debt securities to GDP (%)	Q	$std\Delta yoy$	0.15
Outstanding domestic public debt securities to GDP (%)	Q	$std\Delta yoy$	-0.25
Outstanding international private debt securities to GDP (%)	Q	$std\Delta yoy$	0.08
Outstanding international public debt securities to GDP (%)	Q	$std\Delta yoy$	-0.28
Debt securities by all issuers, amt outstanding, mln LCU	Q	$std\%\Delta yoy$	0.07
International debt securities by all issuers, amt outstanding, mln LCU	Q	$std\%\Delta yoy$	0.01

GBR $FC_B^{(4)}$	Attr.	Trans.	A/B
f_{t-1}			1.02
Treasury Bill Rate, % pa	P	std	0.07
10Y-3M government bond spread, pp	R	std	-0.04
Outstanding domestic private debt securities to GDP (%)	Q	std	-0.02
Outstanding domestic public debt securities to GDP (%)	Q	std	-0.08
Outstanding international private debt securities to GDP (%)	Q	std	-0.10
Outstanding international public debt securities to GDP (%)	Q	std	0.04
Debt securities by all issuers, amt outstanding, mln LCU	Q	std	-0.08
International debt securities by all issuers, amt outstanding, mln LCU	Q	std	-0.11

GBR $FC_{EQ}^{(1)}$	Attr.	Trans.	A/B
Average stock market index value	P	*std%Δyoy*	(hp)

GBR $FC_{EQ}^{(2)}$	Attr.	Trans.	A/B
Average stock market index value	P	*std*	(hp)

GBR $FC_{EQ}^{(3)}$	Attr.	Trans.	A/B
f_{t-1}			0.85
Average stock market index value	P	*std%Δyoy*	0.25
Stock market capitalization to GDP (%)	Q	*stdΔyoy*	0.45
Stock market total value traded to GDP (%)	Q	*stdΔyoy*	0.32
Stock market turnover ratio (%)	Q	*stdΔyoy*	-0.01
Stock price volatility	R	*stdΔyoy*	-0.26

GBR $FC_{EQ}^{(4)}$	Attr.	Trans.	A/B
f_{t-1}			0.99
Average stock market index value	P	*std*	0.12
Stock market capitalization to GDP (%)	Q	*std*	0.08
Stock market total value traded to GDP (%)	Q	*std*	0.13
Stock market turnover ratio (%)	Q	*std*	0.11
Stock price volatility	R	*std*	0.06

GBR $FC_{AG}^{(1)}$	Attr.	Trans.	A/B
f_{t-1}			0.93
Average stock market index value	P	*std%Δyoy*	0.00
Treasury Bill Rate, % pa	P	*stdΔyoy*	0.14
10Y-3M government bond spread	R	*std*	-0.24
Outstanding international public debt securities to GDP (%)	Q	*stdΔyoy*	-0.20
Outstanding international private debt securities to GDP (%)	Q	*stdΔyoy*	0.05
Household Variable Mortgage Rate	P	*stdΔyoy*	0.17
Property prices, real, index, 2010 = 100	P	*std%Δyoy*	0.20
Price to rent ratio	P	*stdΔyoy*	0.19
Total credit to private non-financial sector, % of GDP	Q	*stdΔyoy*	0.27
Private credit by banks, LCU	Q	*std%Δyoy*	0.17
Lending interest rate, % pa	P	*stdΔyoy*	0.03
Money market interest rate, % pa	P	*stdΔyoy*	0.04
Spread between 3-month and overnight interbank interest rate, pp	Q	*std*	-0.01
Spread between lending interest rate and treasury bill rate, pp	R	*std*	0.00

GBR $FC_{AG}^{(2)}$	Attr.	Trans.	A/B
f_{t-1}			0.96
$FC_{CR}^{(1)}$	C	*std*	0.22
$FC_{H}^{(1)}$	C	*std*	0.16
$FC_{B}^{(1)}$	C	*std*	0.22
$FC_{EQ}^{(1)}$	C	*std*	0.00

Table 5: Factor loadings and autoregressive coefficients: DEU

Note: The table shows factor loadings (vector B) from the dynamic factor model associated with the corresponding segment-specific or aggregate financial cycles. f_{t-1} denotes the autoregressive coefficient (A) of the latent factor (financial cycle index). **Attr.** indicates the market attribute the variable captures: *(P)rice, (Q)uantity, (R)isk.* **Trans.** reports the transformations applied to the input signal variables: *std*—standardization, Δyoy—year-on-year difference, $std\%\Delta yoy$—year-on-year percent change.

DEU $FC_{CR}^{(1)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.76
Total credit to private non-financial sector, % of GDP	Q	$std\Delta yoy$	0.16
Private credit by banks, LCU	Q	$std\%\Delta yoy$	0.19
3-month interbank rate, % pa	P	$std\Delta yoy$	0.53
Money market interest rate, % pa	P	$std\Delta yoy$	0.52
Spread between money market rate and treasury bond rate, pp	R	*std*	0.24
Spread between 3-month and overnight interbank rates, pp	R	*std*	0.09

DEU $FC_{CR}^{(2)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.99
Total credit to private non-financial sector, % of GDP	Q	*std*	0.16
Private credit by banks, LCU	Q	*std*	0.15
3-month interbank rate, % pa	P	*std*	0.07
Money market interest rate, % pa	P	*std*	0.09
Spread between money market rate and treasury bond rate, pp	R	*std*	0.09
Spread between 3-month and overnight interbank rates, pp	R	*std*	-0.05

DEU $FC_{CR}^{(3)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.95
Total credit to private non-financial sector, % of GDP	Q	$std\Delta yoy$	0.32
Private credit by banks, LCU	Q	$std\%\Delta yoy$	0.20
3-month interbank rate, % pa	P	$std\Delta yoy$	0.01
Money market interest rate, % pa	P	$std\Delta yoy$	0.02
Spread between money market rate and treasury bond rate, pp	R	*std*	0.02
Spread between 3-month and overnight interbank rates, pp	R	*std*	0.00
Deposit money banks' assets to GDP (%)	Q	$std\Delta yoy$	0.31
Financial system deposits to GDP (%)	Q	$std\Delta yoy$	0.12
Financial system deposits, LCU	Q	$std\%\Delta yoy$	0.13
Deposit money banks' assets, LCU	Q	$std\%\Delta yoy$	0.13
Total credit to Households & NPISHs, % of GDP	Q	$std\Delta yoy$	0.28
Total credit to Households & NPISHs, LCU	Q	$std\%\Delta yoy$	0.23
Total credit to NFCs, % of GDP	Q	$std\Delta yoy$	0.19
Total credit to NFCs, LCU	Q	$std\%\Delta yoy$	0.18
M2, LCU	Q	$std\%\Delta yoy$	0.09

DEU $FC_{CR}^{(4)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			1.00
Total credit to private non-financial sector, % of GDP	Q	*std*	0.06
Private credit by banks, LCU	Q	*std*	0.07
3-month interbank rate, % pa	P	*std*	-0.02
Money market interest rate, % pa	P	*std*	-0.02
Spread between money market rate and treasury bond rate, pp	R	*std*	0.00
Spread between 3-month and overnight interbank rates, pp	R	*std*	-0.01
Deposit money banks' assets to GDP (%)	Q	*std*	0.05
Financial system deposits to GDP (%)	Q	*std*	0.05
Financial system deposits, LCU	Q	*std*	0.06
Deposit money banks' assets, LCU	Q	*std*	0.06
Total credit to Households & NPISHs, % of GDP	Q	*std*	0.06
Total credit to Households & NPISHs, LCU	Q	*std*	0.06
Total credit to NFCs, % of GDP	Q	*std*	0.06
Total credit to NFCs, LCU	Q	*std*	0.06
M2, LCU	Q	*std*	0.04

DEU $FC_H^{(1)}$	Attr.	Trans.	A/B
f_{t-1}			0.95
Property prices, real, index, 2010 = 100	P	$std\%\Delta yoy$	0.31
Price to rent ratio	P	$std\Delta yoy$	0.30

DEU $FC_H^{(2)}$	Attr.	Trans.	A/B
f_{t-1}			0.99
Property prices, real, index, 2010 = 100	P	std	0.13
Price to rent ratio	P	std	0.13

DEU $FC_H^{(3)}$	Attr.	Trans.	A/B
f_{t-1}			0.97
Property prices, real, index, 2010 = 100	P	$std\%\Delta yoy$	0.25
Price to rent ratio	P	$std\Delta yoy$	0.21
Price to income ratio	P	$std\Delta yoy$	0.25
Bank mortgage loans to domestic households and non-profit institutions	Q	$std\%\Delta yoy$	0.07

DEU $FC_H^{(4)}$	Attr.	Trans.	A/B
f_{t-1}			0.99
Property prices, real, index, 2010 = 100	P	std	0.11
Price to rent ratio	P	std	0.10
Price to income ratio	P	std	0.10
Bank mortgage loans to domestic households and non-profit institutions	Q	std	0.11

DEU $FC_B^{(1)}$	Attr.	Trans.	A/B
f_{t-1}			0.84
Corporate - government bond yield spread	R	std	-0.04
Government Bonds Interest Rate, % pa	P	$std\Delta yoy$	0.48
Yields on corporate bonds issued by residents, % pa	P	$std\Delta yoy$	0.47

DEU $FC_B^{(2)}$	Attr.	Trans.	A/B
f_{t-1}			0.99
Corporate - government bond yield spread	R	std	-0.10
Government Bonds Interest Rate, % pa	P	std	0.14
Yields on corporate bonds issued by residents, % pa	P	std	0.12

DEU $FC_B^{(3)}$	Attr.	Trans.	A/B
f_{t-1}			0.91
Corporate - government bond yield spread	R	std	-0.27
Government Bonds Interest Rate, % pa	P	$std\Delta yoy$	0.04
Yields on corporate bonds issued by residents, % pa	P	$std\Delta yoy$	-0.08
Outstanding domestic private debt securities to GDP (%)	Q	$std\Delta yoy$	0.01
Outstanding domestic public debt securities to GDP (%)	Q	$std\Delta yoy$	0.00
Outstanding international private debt securities to GDP (%)	Q	$std\Delta yoy$	0.44
Outstanding international public debt securities to GDP (%)	Q	$std\Delta yoy$	0.45
Debt securities by all issuers, amt outstanding, mln LCU	Q	$std\%\Delta yoy$	0.13
International debt securities by all issuers, amt outstanding, mln LCU	Q	$std\%\Delta yoy$	0.07

DEU $FC_B^{(4)}$	Attr.	Trans.	A/B
f_{t-1}			1.01
Corporate - government bond yield spread	R	std	-0.07
Government Bonds Interest Rate, % pa	P	std	0.06
Yields on corporate bonds issued by residents, % pa	P	std	0.04
Outstanding domestic private debt securities to GDP (%)	Q	std	0.07
Outstanding domestic public debt securities to GDP (%)	Q	std	-0.08
Outstanding international private debt securities to GDP (%)	Q	std	-0.08
Outstanding international public debt securities to GDP (%)	Q	std	-0.09
Debt securities by all issuers, amt outstanding, mln LCU	Q	std	-0.07
International debt securities by all issuers, amt outstanding, mln LCU	Q	std	-0.09

DEU $\boldsymbol{FC_{EQ}^{(1)}}$	**Attr.**	**Trans.**	**A/B**
Average stock market index value	P	$std\%\Delta yoy$	(hp)

DEU $\boldsymbol{FC_{EQ}^{(2)}}$	**Attr.**	**Trans.**	**A/B**
Average stock market index value	P	std	(hp)

DEU $\boldsymbol{FC_{EQ}^{(3)}}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.90
Average stock market index value	P	$std\%\Delta yoy$	0.25
Standard deviation of daily stock market returns	R	std	-0.13
Average daily stock market return	P	std	0.03
Stock market capitalization to GDP (%)	Q	$std\Delta yoy$	0.41
Stock market total value traded to GDP (%)	Q	$std\Delta yoy$	0.35
Stock market turnover ratio (%)	Q	$std\Delta yoy$	0.22
Stock price volatility	R	$std\Delta yoy$	-0.11

DEU $\boldsymbol{FC_{EQ}^{(4)}}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.98
Average stock market index value	P	std	0.17
Standard deviation of daily stock market returns	R	std	0.07
Average daily stock market return	P	std	-0.03
Stock market capitalization to GDP (%)	Q	std	0.18
Stock market total value traded to GDP (%)	Q	std	0.18
Stock market turnover ratio (%)	Q	std	0.11
Stock price volatility	R	std	0.07

DEU $\boldsymbol{FC_{AG}^{(1)}}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.85
Private credit by banks, LCU	Q	$std\Delta yoy$	0.14
Total credit to private non-financial sector, % of GDP	Q	$std\%\Delta yoy$	0.00
3-Month Interbank Rates, % pa	P	$std\Delta yoy$	0.37
Money market interest rate, % pa	P	$std\Delta yoy$	0.34
Spread between money market and government bond rate, pp	R	$std\Delta yoy$	0.23
Spread between 3-month and overnight interbank rates, pp	R	$std\%\Delta yoy$	0.12
Corporate - government bond yield spread	R	std	0.09
Government Bonds Interest Rate, % pa	P	$std\Delta yoy$	0.42
Yields on corporate bonds issued by residents, % pa	P	$std\Delta yoy$	0.46
Property prices, real, index, 2010 = 100	P	$std\%\Delta yoy$	0.22
Price to rent ratio	P	$std\Delta yoy$	0.33
Average stock market index value	P	$std\%\Delta yoy$	-0.13

DEU $\boldsymbol{FC_{AG}^{(2)}}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.88
$FC_{CR}^{(1)}$	C	std	0.32
$FC_{H}^{(1)}$	C	std	0.28
$FC_{B}^{(1)}$	C	std	0.39
$FC_{EQ}^{(1)}$	C	std	-0.14

Table 6: Factor loadings and autoregressive coefficients: JPN

Note: The table shows factor loadings (vector B) from the dynamic factor model associated with the corresponding segment-specific or aggregate financial cycles. f_{t-1} denotes the autoregressive coefficient (A) of the latent factor (financial cycle index). **Attr.** indicates the market attribute the variable captures: *(P)rice, (Q)uantity, (R)isk.* **Trans.** reports the transformations applied to the input signal variables: *std*—standardization, Δyoy—year-on-year difference, $std\%\Delta yoy$—year-on-year percent change.

JPN $FC^{(1)}_{CR}$	Attr.	Trans.	A/B
f_{t-1}			0.99
Private credit by banks, % GDP	Q	$std\Delta yoy$	0.06
Private credit by banks, LCU	Q	$std\%\Delta yoy$	0.11
Lending interest rate, % pa	P	$std\Delta yoy$	0.01
Money market interest rate, % pa	P	$std\Delta yoy$	0.01
Spread between lending and deposit interest rates	R	*std*	0.15
Spread between lending interest rate and government bond rate	R	*std*	0.10

JPN $FC^{(2)}_{CR}$	Attr.	Trans.	A/B
f_{t-1}			0.99
Private credit by banks, % GDP	Q	*std*	0.09
Private credit by banks, LCU	Q	*std*	0.11
Lending interest rate, % pa	P	*std*	0.04
Money market interest rate, % pa	P	*std*	0.01
Spread between lending and deposit interest rates	R	*std*	-0.06
Spread between lending interest rate and government bond rate	R	*std*	0.00

JPN $FC^{(3)}_{CR}$	Attr.	Trans.	A/B
f_{t-1}			0.97
Private credit by banks, % GDP	Q	$std\Delta yoy$	0.16
Financial system deposits, % GDP	Q	$std\Delta yoy$	0.13
Deposit money banks' assets, % GDP	Q	$std\Delta yoy$	0.15
Private credit by banks, LCU	Q	$std\%\Delta yoy$	0.21
Financial system deposits, LCU	Q	$std\%\Delta yoy$	0.17
Deposit money banks' assets, LCU	Q	$std\%\Delta yoy$	0.20
Lending interest rate, % pa	P	$std\Delta yoy$	-0.01
Money market interest rate, % pa	P	$std\Delta yoy$	-0.01
Spread between lending interest rate and government bond rate	R	*std*	0.09
Spread between lending and deposit interest rates	R	*std*	0.19
Bank credit to bank deposits (%)	Q	$std\Delta yoy$	0.09
Total credit to Households & NPISHs, % of GDP	Q	$std\Delta yoy$	0.17
Total credit to Households & NPISHs, LCU	Q	$std\%\Delta yoy$	0.22
Total credit to NFCs, % of GDP	Q	$std\Delta yoy$	0.13
Total credit to NFCs, LCU	Q	$std\%\Delta yoy$	0.23
Monetary Base, LCU	Q	$std\%\Delta yoy$	0.03
Ratio of Monetary Base to Broad Money, %	Q	$std\Delta yoy$	-0.10
M2, LCU	Q	$std\%\Delta yoy$	0.06
M1, LCU	Q	$std\%\Delta yoy$	0.20
Broad Money Liabilities, LCU	Q	$std\%\Delta yoy$	-0.09

JPN $FC^{(4)}_{CR}$	Attr.	Trans.	A/B
f_{t-1}			1.00
Private credit by banks, % GDP	Q	*std*	0.03
Financial system deposits, % GDP	Q	*std*	0.05
Deposit money banks' assets, % GDP	Q	*std*	0.04
Private credit by banks, LCU	Q	*std*	0.05
Financial system deposits, LCU	Q	*std*	0.05
Deposit money banks' assets, LCU	Q	*std*	0.05
Lending interest rate, % pa	P	*std*	0.01
Money market interest rate, % pa	P	*std*	0.00
Spread between lending interest rate and government bond rate	R	*std*	-0.04
Spread between lending and deposit interest rates	R	*std*	-0.01
Bank credit to bank deposits (%)	Q	*std*	-0.04
Total credit to Households & NPISHs, % of GDP	Q	*std*	0.05
Total credit to Households & NPISHs, LCU	Q	*std*	0.05
Total credit to NFCs, % of GDP	Q	*std*	0.03
Total credit to NFCs, LCU	Q	*std*	0.05
Monetary Base, LCU	Q	*std*	0.03

Ratio of Monetary Base to Broad Money, %	Q	*std*	-0.01
M2, LCU	Q	*std*	0.04
M1, LCU	Q	*std*	0.05
Broad Money Liabilities, LCU	Q	*std*	0.03

JPN $FC_H^{(1)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.94
Property prices, real, index, 2010 = 100	P	$std\%\Delta yoy$	0.27
Price to rent ratio	P	$std\Delta yoy$	0.32
Price to income ratio	P	$std\Delta yoy$	0.30

JPN $FC_H^{(2)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.99
Property prices, real, index, 2010 = 100	P	*std*	0.07
Price to rent ratio	P	*std*	0.13
Price to income ratio	P	*std*	0.13

JPN $FC_H^{(3)}$	**Attr.**	**Trans.**	**A/B**
Property prices, real, index, 2010 = 100, standardized	P	*std*	(hp)

$FC_B^{(1)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.92
10Y-3M government bond spread	R	*std*	0.02
Treasury Bill Rate, % pa	P	$std\Delta yoy$	0.19
Outstanding international public debt securities to GDP (%)	Q	$std\Delta yoy$	0.31
Outstanding international private debt securities to GDP (%)	Q	$std\Delta yoy$	0.33

JPN $FC_B^{(2)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			1.00
Treasury Bill Rate, % pa	P	*std*	0.11
10Y-3M government bond spread	R	*std*	-0.10
Outstanding international public debt securities to GDP (%)	Q	*std*	-0.13
Outstanding international private debt securities to GDP (%)	Q	*std*	0.10

JPN $FC_B^{(3)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.93
Treasury Bill Rate, % pa	P	$std\Delta yoy$	0.01
10Y-3M government bond spread	R	*std*	-0.06
Outstanding domestic private debt securities to GDP (%)	Q	$std\Delta yoy$	-0.31
Outstanding domestic public debt securities to GDP (%)	Q	$std\Delta yoy$	-0.34
Outstanding international private debt securities to GDP (%)	Q	$std\Delta yoy$	0.08
Outstanding international public debt securities to GDP (%)	Q	$std\Delta yoy$	0.31
Debt securities by all issuers, amt outstanding, mln LCU	Q	$std\%\Delta yoy$	-0.31
International debt securities by all issuers, amt outstanding, mln LCU	Q	$std\%\Delta yoy$	0.01

JPN $FC_B^{(4)}$	**Attr.**	**Trans.**	**A/B**
f_{t-1}			0.99
Treasury Bill Rate, % pa	P	*std*	0.09
10Y-3M government bond spread	R	*std*	0.07
Outstanding domestic private debt securities to GDP (%)	Q	*std*	-0.07
Outstanding domestic public debt securities to GDP (%)	Q	*std*	-0.08
Outstanding international private debt securities to GDP (%)	Q	*std*	-0.02
Outstanding international public debt securities to GDP (%)	Q	*std*	0.05
Debt securities by all issuers, amt outstanding, mln LCU	Q	*std*	-0.05
International debt securities by all issuers, amt outstanding, mln LCU	Q	*std*	-0.04

JPN $FC_{EQ}^{(1)}$	Attr.	Trans.	A/B
f_{t-1}			0.90
Average stock market index value	P	$std\%\Delta yoy$	0.27
Standard deviation of daily stock market returns, quarterly avg	R	std	-0.25
Average stock market index daily return, quarterly avg	P	std	0.12

JPN $FC_{EQ}^{(2)}$	Attr.	Trans.	A/B
f_{t-1}			0.99
Average stock market index value	P	std	0.16
Standard deviation of daily stock market returns, quarterly avg	R	std	0.13
Average stock market index daily return, quarterly avg	P	std	0.00

JPN $FC_{EQ}^{(3)}$	Attr.	Trans.	A/B
f_{t-1}			0.90
Average stock market index value	P	$std\%\Delta yoy$	0.32
Standard deviation of daily stock market returns, quarterly avg	R	std	-0.11
Average stock market index daily return, quarterly avg	P	std	0.14
Stock market turnover ratio (%)	Q	$std\Delta yoy$	-0.05
Stock market capitalization to GDP (%)	Q	$std\Delta yoy$	0.36

JPN $FC_{EQ}^{(4)}$	Attr.	Trans.	A/B
f_{t-1}			0.98
Average stock market index value	P	std	0.18
Standard deviation of daily stock market returns, quarterly avg	R	std	0.17
Average stock market index daily return, quarterly avg	P	std	0.00
Stock market turnover ratio (%)	Q	std	-0.08
Stock market capitalization to GDP (%)	Q	std	0.18

JPN $FC_{AG}^{(1)}$	Attr.	Trans.	A/B
f_{t-1}			0.97
Average stock market index value	P	$std\%\Delta yoy$	0.09
Standard deviation of daily stock market returns, quarterly avg	R	std	0.02
Average stock market index daily return, quarterly avg	P	std	0.04
10Y-3M government bond spread	R	std	0.11
Treasury Bill Rate, % pa	P	$std\Delta yoy$	0.03
Outstanding international public debt securities to GDP (%)	Q	$std\Delta yoy$	0.11
Outstanding international private debt securities to GDP (%)	Q	$std\Delta yoy$	0.11
Property prices, real, index, 2010 = 100	P	$std\%\Delta yoy$	0.11
Price to rent ratio	P	$std\Delta yoy$	0.11
Price to income ratio	P	$std\Delta yoy$	0.07
Private credit by banks, % GDP	Q	$std\Delta yoy$	0.13
Private credit by banks, LCU	Q	$std\%\Delta yoy$	0.14
Lending interest rate, % pa	Q	$std\Delta yoy$	0.01
Money market interest rate, % pa	P	$std\Delta yoy$	0.01
Spread between lending and deposit interest rates	R	std	0.17
Spread between lending interest rate and government bond rate	R	std	0.09

JPN $FC_{AG}^{(2)}$	Attr.	Trans.	A/B
f_{t-1}			0.98
$FC_{CR}^{(1)}$	C	std	0.15
$FC_{H}^{(1)}$	C	std	0.07
$FC_{B}^{(1)}$	C	std	0.08
$FC_{EQ}^{(1)}$	C	std	0.10

Table 7: Turning points, phase and cycle duration: USA

Note: tp – turning point at the reported date: 1=peak, -1=trough; ϕ – phase of the financial cycle, ending at the reported date: 1=expansion, 0=contraction; τ_{phase} – phase duration (time between the current and the previous turning point), in quarters; τ_{cycle} – cycle duration (time between the current peak/trough and the previous peak/trough), in quarters.

$FC^{(1)}_{CR}$

$date$	tp	ϕ	τ_{phase}	τ_{cycle}
1965q2	1	1		
1967q2	-1	0	8	
1969q2	1	1	8	16
1971q1	-1	0	7	15
1973q2	1	1	9	16
1975q2	-1	0	8	17
1978q2	1	1	12	20
1982q3	-1	0	17	29
1984q3	1	1	8	25
1991q3	-1	0	28	36
1995q2	1	1	15	43
2001q4	-1	0	26	41
2005q3	1	1	15	41
2009q3	-1	0	16	31

$\widehat{FC}^{*(1)}_{CR}$

$date$	tp	ϕ	τ_{phase}	τ_{cycle}
1965q1	1	1		
1968q1	-1	0	12	
1973q1	1	1	20	32
1975q4	-1	0	11	31
1978q1	1	1	9	20
1982q1	-1	0	16	25
1986q3	1	1	18	34
1991q4	-1	0	21	39
1997q4	1	1	24	45
2000q4	-1	0	12	36
2005q2	1	1	18	30
2010q3	-1	0	21	39

$FC^{(1)}_{H}$

$date$	tp	ϕ	τ_{phase}	τ_{cycle}
1975q3	-1	0		
1978q1	1	1	10	
1981q3	-1	0	14	24
1986q4	1	1	21	35
1990q4	-1	0	16	37
2005q2	1	1	58	74
2008q3	-1	0	13	71
2013q3	1	1	20	33

$\widehat{FC}^{*(1)}_{H}$

$date$	tp	ϕ	τ_{phase}	τ_{cycle}
1975q2	-1	0		
1977q3	1	1	9	
1981q4	-1	0	17	26
1986q4	1	1	20	37
1992q4	-1	0	24	44
2003q2	1	1	42	66
2009q3	-1	0	25	67

$FC^{(1)}_{B}$

$date$	tp	ϕ	τ_{phase}	τ_{cycle}
1966q3	1	1		
1967q3	-1	0	4	
1969q4	1	1	9	13
1971q2	-1	0	6	15
1973q4	1	1	10	16
1976q3	-1	0	11	21
1981q2	1	1	19	30
1983q1	-1	0	7	26
1989q1	1	1	24	31
1992q3	-1	0	14	38
2000q2	1	1	31	45
2002q1	-1	0	7	38
2006q3	1	1	18	25
2009q3	-1	0	12	30
2013q3	1	1	16	28

$\widehat{FC}^{*(1)}_{B}$

$date$	tp	ϕ	τ_{phase}	τ_{cycle}
1967q1	1	1		
1972q1	-1	0	20	
1973q4	1	1	7	27
1975q2	-1	0	6	13
1980q2	1	1	20	26
1985q4	-1	0	22	42
1989q3	1	1	15	37
1992q3	-1	0	12	27
1998q2	1	1	23	35
2002q3	-1	0	17	40
2006q2	1	1	15	32
2011q1	-1	0	19	34

$FC^{(1)}_{EQ}$

$date$	tp	ϕ	τ_{phase}	τ_{cycle}
1964q1	1	1		
1966q3	-1	0	10	
1967q3	1	1	4	14
1970q2	-1	0	11	15
1971q2	1	1	4	15
1974q3	-1	0	13	17
1976q1	1	1	6	19
1982q1	-1	0	24	30
1983q2	1	1	5	29
1988q1	-1	0	19	24
1989q3	1	1	6	25
1994q2	-1	0	19	25
1995q4	1	1	6	25
2002q3	-1	0	27	33
2004q1	1	1	6	33
2008q4	-1	0	19	25

$\widehat{FC}^{*(1)}_{EQ}$

$date$	tp	ϕ	τ_{phase}	τ_{cycle}
1964q4	1	1		
1974q3	-1	0	39	
1985q1	1	1	42	81
1989q2	-1	0	17	59
1996q1	1	1	27	44
2001q4	-1	0	23	50
2005q2	1	1	14	37
2008q4	-1	0	14	28

$FC^{(2)}_{AG}$

$date$	tp	ϕ	τ_{phase}	τ_{cycle}
1973q2	1	1		
1975q2	-1	0	8	
1979q1	1	1	15	23
1982q3	-1	0	14	29
1987q1	1	1	18	32
1991q4	-1	0	19	37
1999q4	1	1	32	51
2002q1	-1	0	9	41
2005q4	1	1	15	24
2009q1	-1	0	13	28

$\widehat{FC}^{*(2)}_{AG}$

$date$	tp	ϕ	τ_{phase}	τ_{cycle}
1975q2	-1	0		
1979q1	1	1	15	
1983q1	-1	0	16	31
1986q4	1	1	15	31
1992q1	-1	0	21	36
1998q2	1	1	25	46
2001q2	-1	0	12	37
2004q4	1	1	14	26
2010q1	-1	0	21	35

Table 8: Turning points, phase and cycle duration: GBR

Note: *tp* – turning point at the reported date: 1=peak, -1=trough; ϕ – phase of the financial cycle, ending at the reported date: 1=expansion, 0=contraction; τ_{phase} – phase duration (time between the current and the previous turning point), in quarters; τ_{cycle} – cycle duration (time between the current peak/trough and the previous peak/trough), in quarters.

		$\boldsymbol{FC_{CR}^{(1)}}$					$\boldsymbol{\widehat{FC}_{CR}^{*(1)}}$		
date	*tp*	ϕ	τ_{phase}	τ_{cycle}	*date*	*tp*	ϕ	τ_{phase}	τ_{cycle}
1983q2	1	1			1987q2	1	1		
1985q3	-1	0	9		1994q2	-1	0	28	
1987q1	1	1	6	15	2007q1	1	1	51	79
1992q3	-1	0	22	28					
2001q1	1	1	34	56					
2003q4	-1	0	11	45					
2008q4	1	1	20	31					

		$\boldsymbol{FC_{H}^{(1)}}$					$\boldsymbol{\widehat{FC}_{H}^{*(1)}}$		
date	*tp*	ϕ	τ_{phase}	τ_{cycle}	*date*	*tp*	ϕ	τ_{phase}	τ_{cycle}
1973q1	1	1			1972q3	1	1		
1975q3	-1	0	10		1976q3	-1	0	16	
1979q2	1	1	15	25	1979q3	1	1	12	28
1981q3	-1	0	9	24	1981q4	-1	0	9	21
1988q4	1	1	29	38	1987q3	1	1	23	32
1991q3	-1	0	11	40	1992q4	-1	0	21	44
2003q1	1	1	46	57	2002q3	1	1	39	60
2005q4	-1	0	11	57	2009q4	-1	0	29	68
2007q2	1	1	6	17					
2009q1	-1	0	7	13					

		$\boldsymbol{FC_{B}^{(1)}}$					$\boldsymbol{\widehat{FC}_{B}^{*(1)}}$		
date	*tp*	ϕ	τ_{phase}	τ_{cycle}	*date*	*tp*	ϕ	τ_{phase}	τ_{cycle}
1989q2	1	1			1989q1	1	1		
1993q1	-1	0	15		1994q2	-1	0	21	
1998q1	1	1	20	35	2001q2	1	1	28	49
2003q4	-1	0	23	43	2003q3	-1	0	9	37
2007q1	1	1	13	36	2005q2	1	1	7	16
2010q4	-1	0	15	28	2010q4	-1	0	22	29
2012q3	1	1	7	22					

		$\boldsymbol{FC_{EQ}^{(1)}}$					$\boldsymbol{\widehat{FC}_{EQ}^{*(1)}}$		
date	*tp*	ϕ	τ_{phase}	τ_{cycle}	*date*	*tp*	ϕ	τ_{phase}	τ_{cycle}
1962q2	-1	0			1964q3	-1	0		
1963q4	1	1	6		1968q2	1	1	15	
1965q3	-1	0	7	13	1973q4	-1	0	22	37
1968q3	1	1	12	19	1977q4	1	1	16	38
1969q4	-1	0	5	17	1980q3	-1	0	11	27
1972q1	1	1	9	14	1984q3	1	1	16	27
1974q4	-1	0	11	20	1990q4	-1	0	25	41
1975q4	1	1	4	15	1997q2	1	1	26	51
1980q2	-1	0	18	22	2002q2	-1	0	20	46
1987q3	1	1	29	47	2006q2	1	1	16	36
1988q3	-1	0	4	33	2008q4	-1	0	10	26
1993q3	1	1	20	24	2013q1	1	1	17	27
1995q1	-1	0	6	26					
1998q2	1	1	13	19					
2003q1	-1	0	19	32					
2004q1	1	1	4	23					
2008q4	-1	0	19	23					
2010q1	1	1	5	24					
2012q2	-1	0	9	14					
2013q2	1	1	4	13					

		$\boldsymbol{FC_{AG}^{(2)}}$					$\boldsymbol{\widehat{FC}_{AG}^{*(2)}}$		
date	*tp*	ϕ	τ_{phase}	τ_{cycle}	*date*	*tp*	ϕ	τ_{phase}	τ_{cycle}
1989q1	1	1			1988q1	1	1		
1993q1	-1	0	16		1994q1	-1	0	24	
2000q3	1	1	30	46	2002q3	1	1	34	58
2004q1	-1	0	14	44	2011q3	-1	0	36	70
2007q1	1	1	12	26					
2011q1	-1	0	16	28					

Table 9: Turning points, phase and cycle duration: DEU

Note: tp – turning point at the reported date: 1=peak, -1=trough; ϕ – phase of the financial cycle, ending at the reported date: 1=expansion, 0=contraction; τ_{phase} – phase duration (time between the current and the previous turning point), in quarters; τ_{cycle} – cycle duration (time between the current peak/trough and the previous peak/trough), in quarters.

$\boldsymbol{FC^{(1)}_{CR}}$

date	*tp*	ϕ	τ_{phase}	τ_{cycle}
1967q4	-1	0		
1970q1	1	1	9	
1971q2	-1	0	5	14
1973q3	1	1	9	14
1975q1	-1	0	6	15
1981q2	1	1	25	31
1982q3	-1	0	5	30
1984q3	1	1	8	13
1986q1	-1	0	6	14
1989q4	1	1	15	21
1991q3	-1	0	7	22
1992q3	1	1	4	11
1999q2	-1	0	27	31
2000q3	1	1	5	32
2001q4	-1	0	5	10
2008q3	1	1	27	32
2009q3	-1	0	4	31

$\boldsymbol{\widehat{FC}^{*(1)}_{CR}}$

date	*tp*	ϕ	τ_{phase}	τ_{cycle}
1968q1	-1	0		
1972q3	1	1	18	
1975q4	-1	0	13	31
1980q2	1	1	18	31
1985q4	-1	0	22	40
1992q3	1	1	27	49
1996q2	-1	0	15	42
2000q1	1	1	15	30
2003q2	-1	0	13	28
2006q4	1	1	14	27

$\boldsymbol{FC^{(1)}_{H}}$

date	*tp*	ϕ	τ_{phase}	τ_{cycle}
1975q3	-1	0		
1978q4	1	1	13	
1984q2	-1	0	22	35
1990q2	1	1	24	46
1992q1	-1	0	7	31
1994q2	1	1	9	16
1997q1	-1	0	11	20
2000q2	1	1	13	24
2003q3	-1	0	13	26
2012q1	1	1	34	47

$\boldsymbol{\widehat{FC}^{*(1)}_{H}}$

date	*tp*	ϕ	τ_{phase}	τ_{cycle}
1974q4	-1	0		
1979q1	1	1	17	
1984q2	-1	0	21	38
1990q3	1	1	25	46
1997q2	-1	0	27	52
1999q4	1	1	10	37
2005q1	-1	0	21	31

$\boldsymbol{FC^{(1)}_{B}}$

date	*tp*	ϕ	τ_{phase}	τ_{cycle}
1966q2	1	1		
1967q3	-1	0	5	
1970q2	1	1	11	16
1971q4	-1	0	6	17
1973q3	1	1	7	13
1975q3	-1	0	8	15
1981q3	1	1	24	32
1982q4	-1	0	5	29
1990q3	1	1	31	36
1993q3	-1	0	12	43
1994q4	1	1	5	17
1998q4	-1	0	16	21
2000q1	1	1	5	21
2003q2	-1	0	13	18
2007q3	1	1	17	30
2009q4	-1	0	9	26

$\boldsymbol{\widehat{FC}^{*(1)}_{B}}$

date	*tp*	ϕ	τ_{phase}	τ_{cycle}
1965q3	1	1		
1967q4	-1	0	9	
1971q3	1	1	15	24
1976q3	-1	0	20	35
1980q3	1	1	16	36
1984q4	-1	0	17	33
1989q4	1	1	20	37
1995q4	-1	0	24	44
2000q3	1	1	19	43
2003q3	-1	0	12	31
2007q2	1	1	15	27
2012q2	-1	0	20	35

$\boldsymbol{FC^{(1)}_{EQ}}$

date	*tp*	ϕ	τ_{phase}	τ_{cycle}
1966q3	-1	0		
1968q2	1	1	7	
1970q4	-1	0	10	17
1972q4	1	1	8	18
1974q1	-1	0	5	13
1975q4	1	1	7	12
1979q4	-1	0	16	23
1986q1	1	1	25	41
1987q4	-1	0	7	32
1990q1	1	1	9	16
1991q1	-1	0	4	13
1997q3	1	1	26	30
2003q1	-1	0	22	48
2004q1	1	1	4	26
2008q4	-1	0	19	23
2010q1	1	1	5	24

$\boldsymbol{\widehat{FC}^{*(1)}_{EQ}}$

date	*tp*	ϕ	τ_{phase}	τ_{cycle}
1968q3	1	1		
1973q4	-1	0	21	
1976q1	1	1	9	30
1979q3	-1	0	14	23
1985q1	1	1	22	36
1991q4	-1	0	27	49
1997q3	1	1	23	50
2002q2	-1	0	19	42
2006q2	1	1	16	35
2009q3	-1	0	13	29

$\boldsymbol{FC^{(2)}_{AG}}$

date	*tp*	ϕ	τ_{phase}	τ_{cycle}
1973q3	1	1		
1975q3	-1	0	8	
1979q4	1	1	17	25
1983q1	-1	0	13	30
1990q2	1	1	29	42
1997q3	-1	0	29	58
2000q2	1	1	11	40
2004q1	-1	0	15	26
2008q2	1	1	17	32
2009q4	-1	0	6	23

$\boldsymbol{\widehat{FC}^{*(2)}_{AG}}$

date	*tp*	ϕ	τ_{phase}	τ_{cycle}
1975q4	-1	0		
1980q1	1	1	17	
1984q4	-1	0	19	36
1990q3	1	1	23	42
1996q4	-1	0	25	48
2000q4	1	1	16	41
2004q2	-1	0	14	30
2008q1	1	1	15	29
2009q4	-1	0	7	22

Table 10: Turning points, phase and cycle duration: JPN

Note: tp – turning point at the reported date: 1=peak, -1=trough; ϕ – phase of the financial cycle, ending at the reported date: 1=expansion, 0=contraction; τ_{phase} – phase duration (time between the current and the previous turning point), in quarters; τ_{cycle} – cycle duration (time between the current peak/trough and the previous peak/trough), in quarters.

$\boldsymbol{FC^{(1)}_{CR}}$

date	tp	ϕ	τ_{phase}	τ_{cycle}
1967q3	-1	0		
1970q4	1	1	13	
1973q3	-1	0	11	24
1975q4	1	1	9	20
1980q1	-1	0	17	26
1981q4	1	1	7	24
1983q3	-1	0	7	14
1987q1	1	1	14	21
2002q2	-1	0	61	75
2004q4	1	1	10	71
2007q2	-1	0	10	20
2009q1	1	1	7	17

$\boldsymbol{\widehat{FC}^{*(1)}_{CR}}$

date	tp	ϕ	τ_{phase}	τ_{cycle}
1967q3	-1	0		
1975q3	1	1	32	
1981q2	-1	0	23	55
1988q2	1	1	28	51
2002q2	-1	0	56	84

$\boldsymbol{FC^{(1)}_{H}}$

date	tp	ϕ	τ_{phase}	τ_{cycle}
1973q3	1	1		
1975q2	-1	0	7	
1980q1	1	1	19	26
1985q3	-1	0	22	41
1990q3	1	1	20	42
1992q4	-1	0	9	29
1998q3	1	1	23	32
2004q3	-1	0	24	47
2008q2	1	1	15	39
2009q2	-1	0	4	19
2010q4	1	1	6	10

$\boldsymbol{\widehat{FC}^{*(1)}_{H}}$

date	tp	ϕ	τ_{phase}	τ_{cycle}
1976q2	-1	0		
1981q4	1	1	22	
1984q4	-1	0	12	34
1989q1	1	1	17	29
1994q1	-1	0	20	37
1999q1	1	1	20	40
2003q4	-1	0	19	39

$\boldsymbol{FC^{(1)}_{B}}$

date	tp	ϕ	τ_{phase}	τ_{cycle}
1986q1	1	1		
1987q1	-1	0	4	
1990q1	1	1	12	16
1993q3	-1	0	14	26
1997q1	1	1	14	28
2000q3	-1	0	14	28
2002q2	1	1	7	21
2004q2	-1	0	8	15
2007q1	1	1	11	19
2011q2	-1	0	17	28

$\boldsymbol{\widehat{FC}^{*(1)}_{B}}$

date	tp	ϕ	τ_{phase}	τ_{cycle}
1989q2	1	1		
1994q1	-1	0	19	
1998q1	1	1	16	35
2002q1	-1	0	16	32
2006q4	1	1	19	35
2010q1	-1	0	13	32

$\boldsymbol{FC^{(1)}_{EQ}}$

date	tp	ϕ	τ_{phase}	τ_{cycle}
1964q2	-1	0		
1969q2	1	1	20	
1970q4	-1	0	6	26
1972q4	1	1	8	14
1974q4	-1	0	8	16
1979q1	1	1	17	25
1982q2	-1	0	13	30
1983q4	1	1	6	19
1990q3	-1	0	27	33
1996q2	1	1	23	50
1997q4	-1	0	6	29
1999q4	1	1	8	14
2001q1	-1	0	5	13
2006q1	1	1	20	25
2008q4	-1	0	11	31
2013q3	1	1	19	30

$\boldsymbol{\widehat{FC}^{*(1)}_{EQ}}$

date	tp	ϕ	τ_{phase}	τ_{cycle}
1964q3	-1	0		
1972q1	1	1	30	
1976q1	-1	0	16	46
1985q1	1	1	36	52
1991q2	-1	0	25	61
1996q2	1	1	20	45
2000q2	-1	0	16	36
2005q1	1	1	19	35
2009q2	-1	0	17	36

$\boldsymbol{FC^{(2)}_{AG}}$

date	tp	ϕ	τ_{phase}	τ_{cycle}
1987q2	1	1		
1993q1	-1	0	23	
1996q3	1	1	14	37
2001q4	-1	0	21	35
2006q3	1	1	19	40
2009q1	-1	0	10	29

$\boldsymbol{\widehat{FC}^{*(2)}_{AG}}$

date	tp	ϕ	τ_{phase}	τ_{cycle}
1987q4	1	1		
1993q3	-1	0	23	
1997q2	1	1	15	38
2001q4	-1	0	18	33
2006q4	1	1	20	38
2009q1	-1	0	9	29

Table 11: Correlation and concordance between financial cycles: USA

concordance index	$FC^{(1)}_{CR}$	$FC^{(1)}_{H}$	$FC^{(1)}_{B}$	$FC^{(1)}_{EQ}$
$FC^{(1)}_{H}$	0.58			
$FC^{(1)}_{B}$	0.58	0.53		
$FC^{(1)}_{EQ}$	0.61	0.42	0.37	
$FC^{(2)}_{AG}$	0.69	0.66	0.80	0.54

correlation index	$FC^{(1)}_{CR}$	$FC^{(1)}_{H}$	$FC^{(1)}_{B}$	$FC^{(1)}_{EQ}$
$FC^{(1)}_{H}$	0.58***			
$FC^{(1)}_{B}$	0.56***	0.06		
$FC^{(1)}_{EQ}$	0.24***	0.24***	0.07	
$FC^{(2)}_{AG}$	0.9***	0.72***	0.61***	0.41***

correlation index	$\Delta FC^{(1)}_{CR}$	$\Delta FC^{(1)}_{H}$	$\Delta FC^{(1)}_{B}$	$\Delta FC^{(1)}_{EQ}$
$\Delta FC^{(1)}_{H}$	0.42***			
$\Delta FC^{(1)}_{B}$	0.56***	0.08		
$\Delta FC^{(1)}_{EQ}$	0.05	0.31***	-0.13*	
$\Delta FC^{(2)}_{AG}$	0.78***	0.67***	0.58***	0.37***

Table 12: Correlation and concordance between financial cycles: GBR

concordance index	$FC^{(1)}_{CR}$	$FC^{(1)}_{H}$	$FC^{(1)}_{B}$	$FC^{(1)}_{EQ}$
$FC^{(1)}_{H}$	0.57			
$FC^{(1)}_{B}$	0.59	0.49		
$FC^{(1)}_{EQ}$	0.25	0.42	0.36	
$FC^{(2)}_{AG}$	0.70	0.58	0.71	0.29

correlation index	$FC^{(1)}_{CR}$	$FC^{(1)}_{H}$	$FC^{(1)}_{B}$	$FC^{(1)}_{EQ}$
$FC^{(1)}_{H}$	0.25***			
$FC^{(1)}_{B}$	0.64***	0.54***		
$FC^{(1)}_{EQ}$	0.08	-0.06	-0.04	
$FC^{(2)}_{AG}$	0.85***	0.67***	0.89***	0.02

correlation index	$\Delta FC^{(1)}_{CR}$	$\Delta FC^{(1)}_{H}$	$\Delta FC^{(1)}_{B}$	$\Delta FC^{(1)}_{EQ}$
$\Delta FC^{(1)}_{H}$	-0.07			
$\Delta FC^{(1)}_{B}$	0.39***	0.31***		
$\Delta FC^{(1)}_{EQ}$	-0.06	0.00	0.01	
$\Delta FC^{(2)}_{AG}$	0.56***	0.53***	0.83***	0.03

Table 13: Correlation and concordance between financial cycles: DEU

concordance index	$FC^{(1)}_{CR}$	$FC^{(1)}_{H}$	$FC^{(1)}_{B}$	$FC^{(1)}_{EQ}$
$FC^{(1)}_{H}$	0.50			
$FC^{(1)}_{B}$	0.76	0.57		
$FC^{(1)}_{EQ}$	0.32	0.40	0.34	
$FC^{(2)}_{AG}$	0.78	0.70	0.87	0.25

correlation index	$FC^{(1)}_{CR}$	$FC^{(1)}_{H}$	$FC^{(1)}_{B}$	$FC^{(1)}_{EQ}$
$FC^{(1)}_{H}$	0.18**			
$FC^{(1)}_{B}$	0.56***	0.35***		
$FC^{(1)}_{EQ}$	-0.05	-0.13*	-0.23***	
$FC^{(2)}_{AG}$	0.7***	0.67***	0.87***	-0.31***

correlation index	$\Delta FC^{(1)}_{CR}$	$\Delta FC^{(1)}_{H}$	$\Delta FC^{(1)}_{B}$	$\Delta FC^{(1)}_{EQ}$
$\Delta FC^{(1)}_{H}$	0.09			
$\Delta FC^{(1)}_{B}$	0.47***	0.42***		
$\Delta FC^{(1)}_{EQ}$	-0.01	-0.01	-0.07	
$\Delta FC^{(2)}_{AG}$	0.71***	0.49***	0.84***	-0.21**

Table 14: Correlation and concordance between financial cycles: JPN

concordance index	$FC^{(1)}_{CR}$	$FC^{(1)}_{H}$	$FC^{(1)}_{B}$	$FC^{(1)}_{EQ}$
$FC^{(1)}_{H}$	0.27			
$FC^{(1)}_{B}$	0.37	0.41		
$FC^{(1)}_{EQ}$	0.41	0.42	0.29	
$FC^{(2)}_{AG}$	0.50	0.41	0.57	0.54

correlation index	$FC^{(1)}_{CR}$	$FC^{(1)}_{H}$	$FC^{(1)}_{B}$	$FC^{(1)}_{EQ}$
$FC^{(1)}_{H}$	0.16**			
$FC^{(1)}_{B}$	0.16*	0.74***		
$FC^{(1)}_{EQ}$	0.37***	0.22***	0.01	
$FC^{(2)}_{AG}$	0.79***	0.66***	0.56***	0.41***

correlation index	$\Delta FC^{(1)}_{CR}$	$\Delta FC^{(1)}_{H}$	$\Delta FC^{(1)}_{B}$	$\Delta FC^{(1)}_{EQ}$
$\Delta FC^{(1)}_{H}$	-0.29***			
$\Delta FC^{(1)}_{B}$	-0.25***	0.47***		
$\Delta FC^{(1)}_{EQ}$	0.04	-0.09	-0.24**	
$\Delta FC^{(2)}_{AG}$	0.32***	0.36***	0.54***	0.32***

Appendix B: Figures

Figure 4: Credit financial cycles: USA

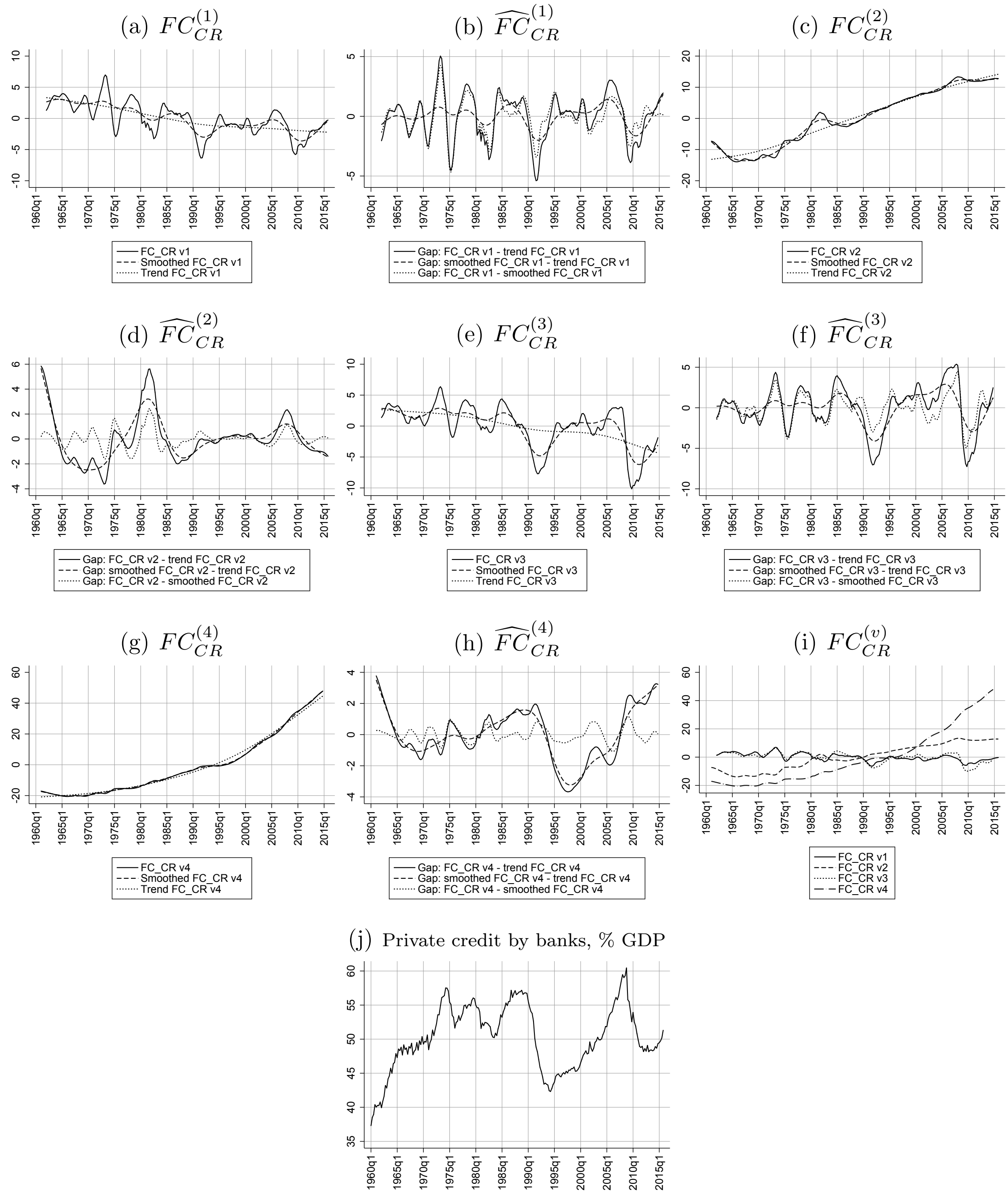
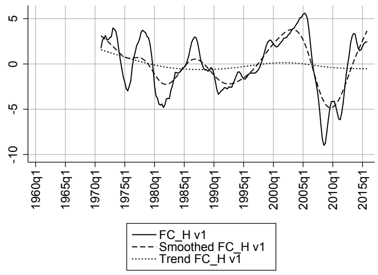
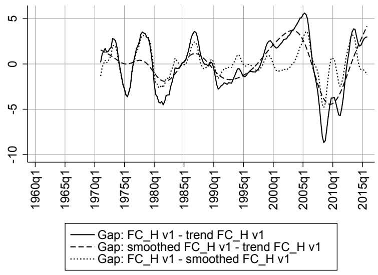


Figure 5: Housing financial cycles: USA

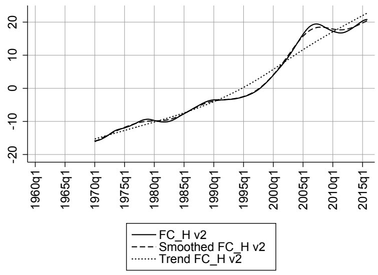
(a) $FC_H^{(1)}$



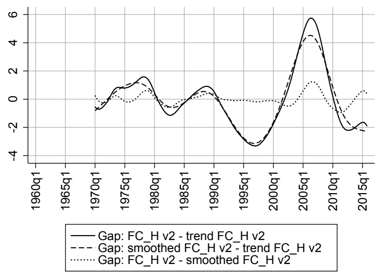
(b) $\widehat{FC}_H^{(1)}$



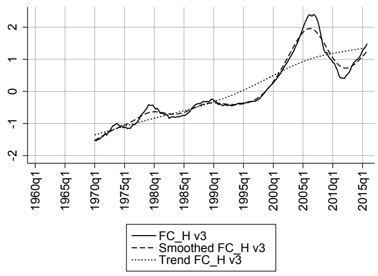
(c) $FC_H^{(2)}$



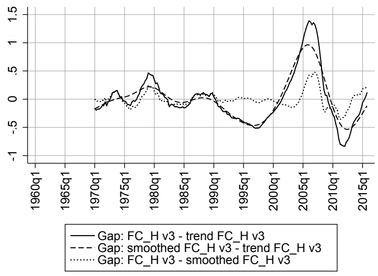
(d) $\widehat{FC}_H^{(2)}$



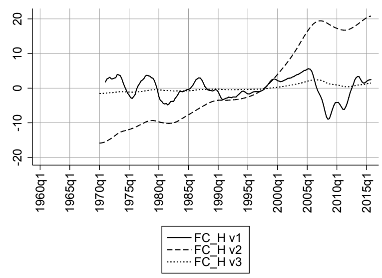
(e) $FC_H^{(3)}$



(f) $\widehat{FC}_H^{(3)}$



(g) $FC_H^{(v)}$



(h) Real housing price index, 2010=100

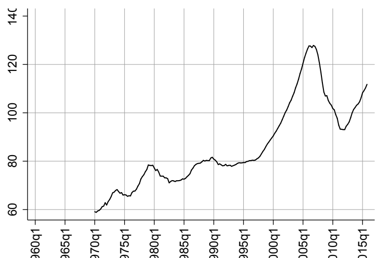


Figure 6: Bond financial cycles: USA

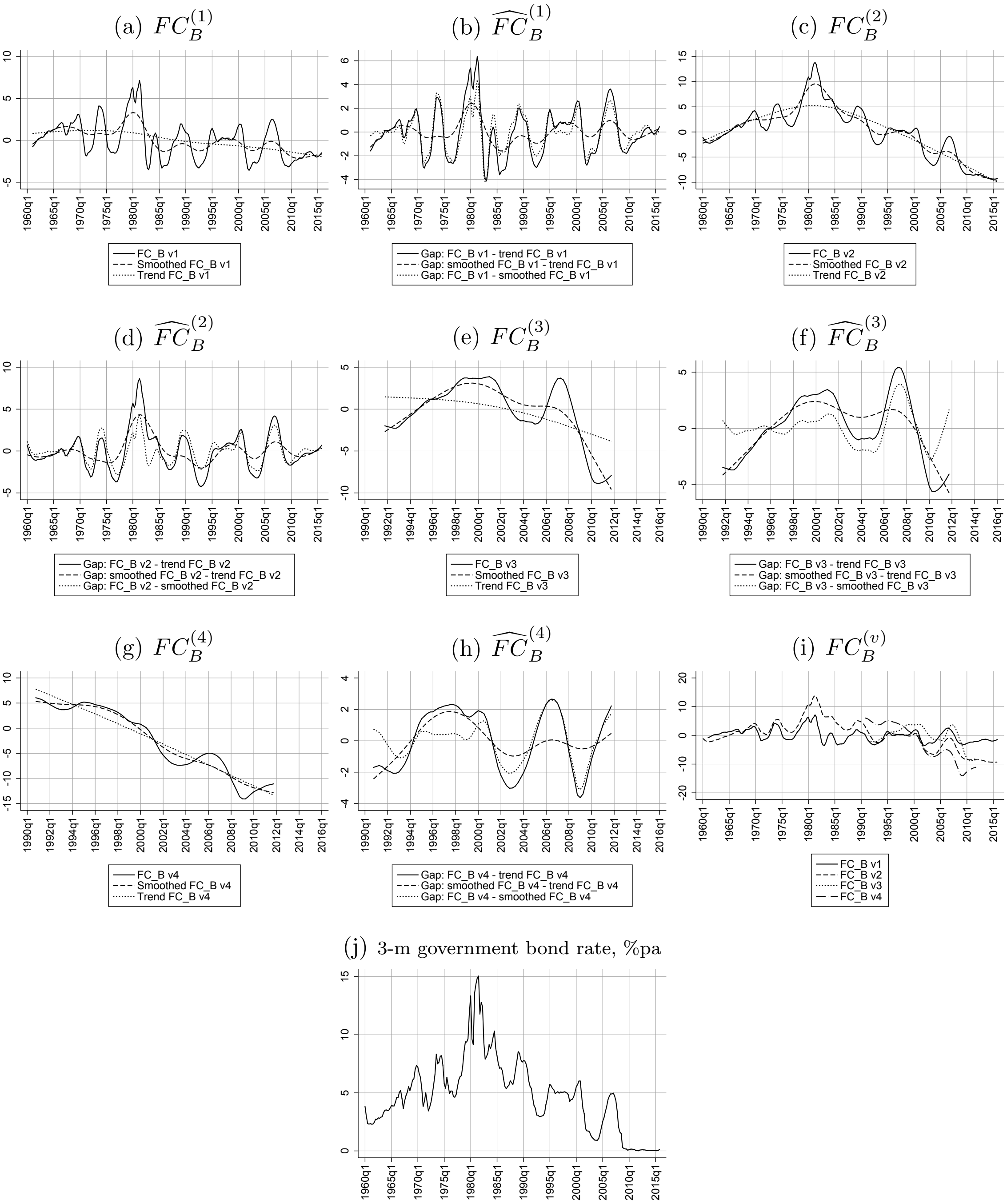
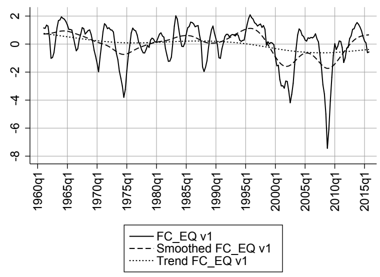
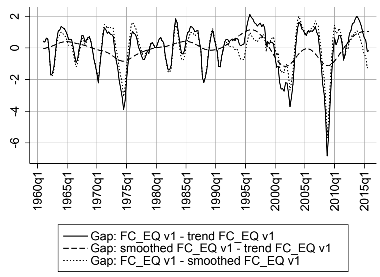


Figure 7: Equity financial cycles: USA

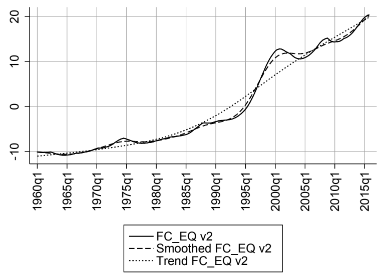
(a) $FC_{EQ}^{(1)}$



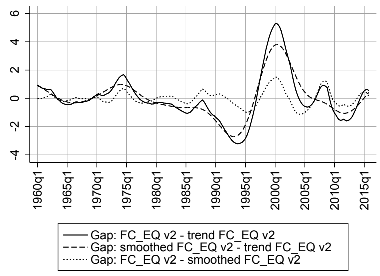
(b) $\widehat{FC}_{EQ}^{(1)}$



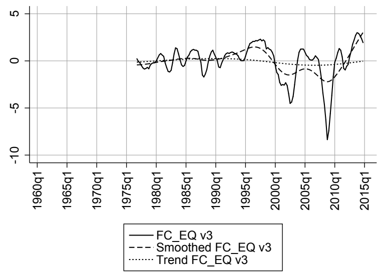
(c) $FC_{EQ}^{(2)}$



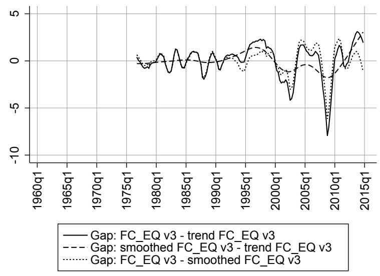
(d) $\widehat{FC}_{EQ}^{(2)}$



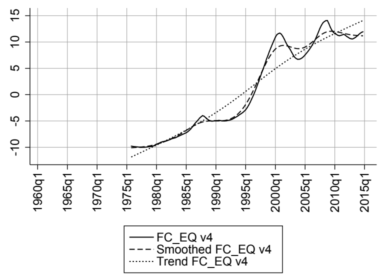
(e) $FC_{EQ}^{(3)}$



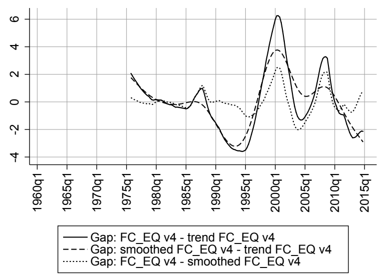
(f) $\widehat{FC}_{EQ}^{(3)}$



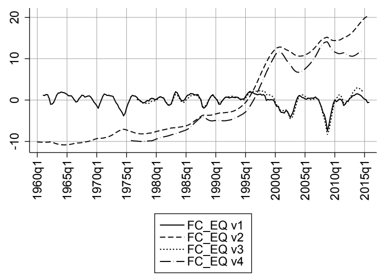
(g) $FC_{EQ}^{(4)}$



(h) $\widehat{FC}_{EQ}^{(4)}$



(i) $FC_{EQ}^{(v)}$



(j) Stock market index, SP500

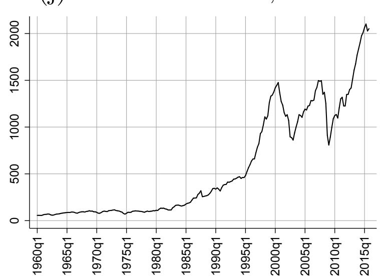


Figure 8: Aggregate financial cycles: USA

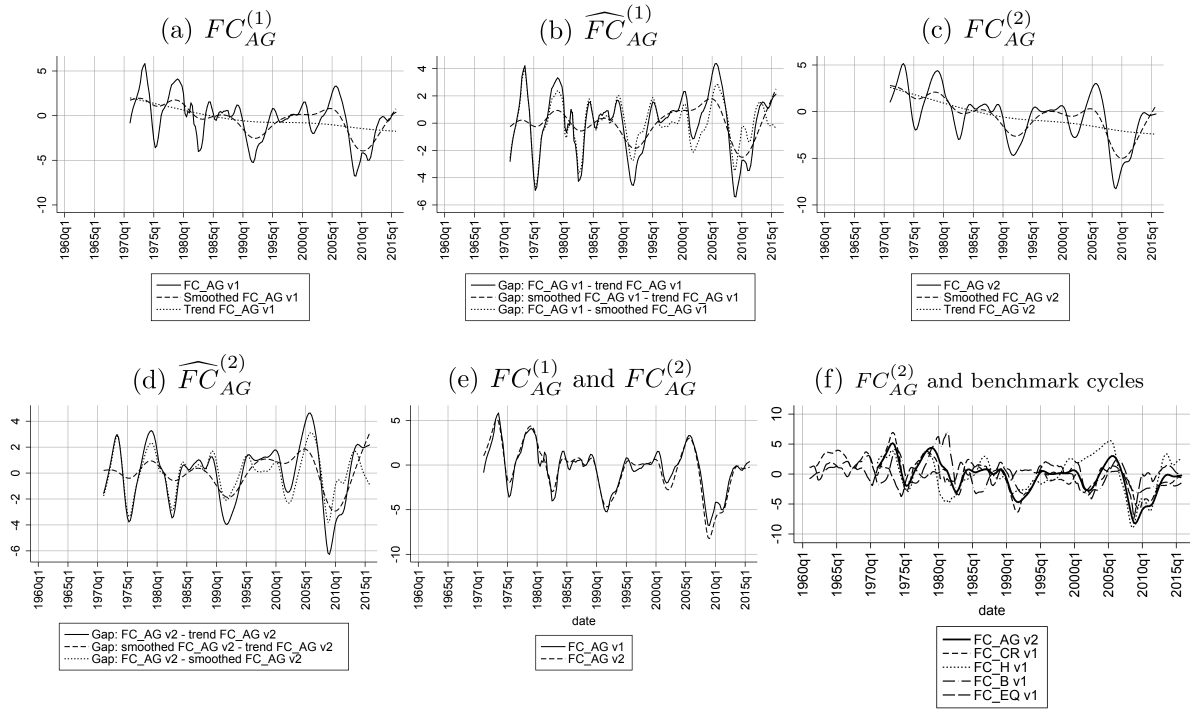


Figure 9: Scatterplot matrix of main financial cycles: USA

Notes: The figure shows scatterplots of the benchmark segment-specific (CR, H, B, EQ) and aggregate (AG) financial cycles in levels and first differences (D).

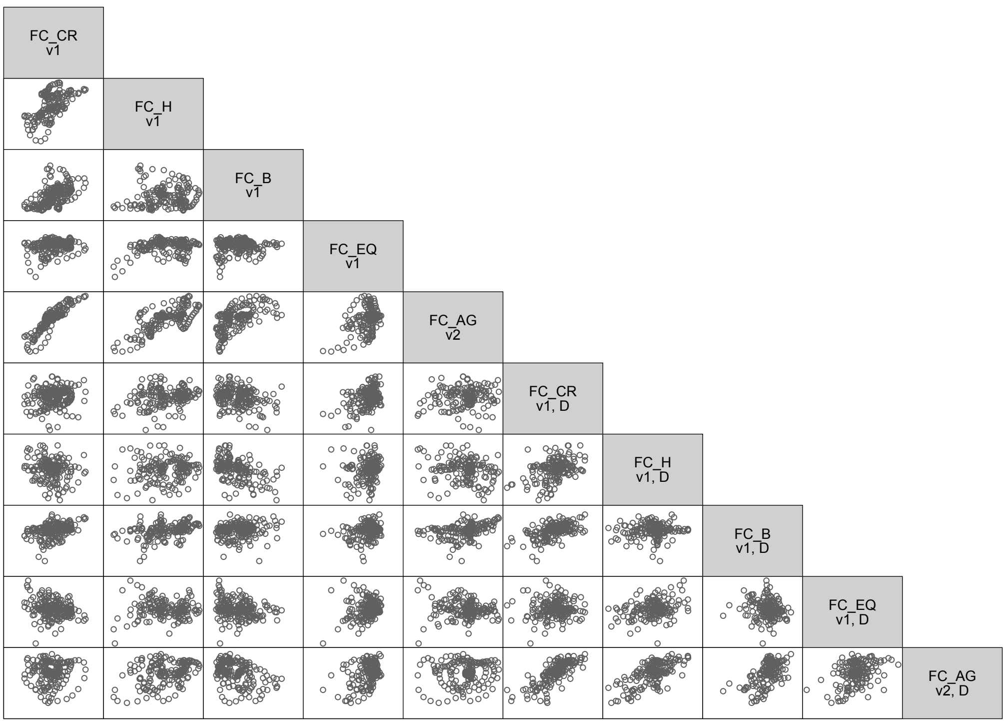
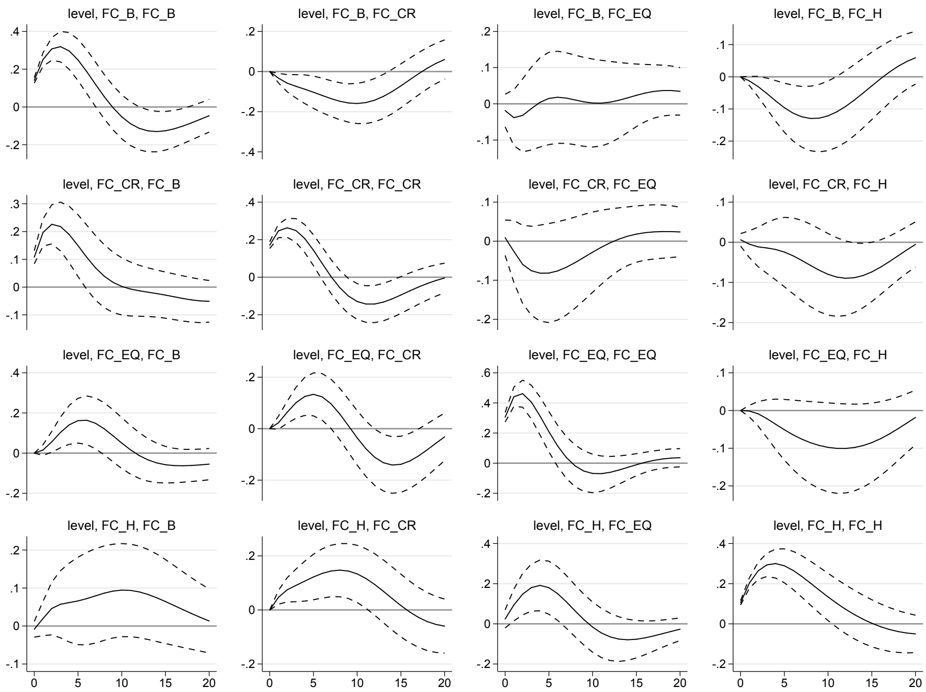


Figure 10: Impulse-response functions: USA

Notes: VAR(K) lag order based on conventional (Akaike, Hannan-Quinn, Schwarz Bayesian) information criteria: $K = 3$ for Model (a)—in gaps (deviations from the trend); $K = 4$ for Model (b)—in first differences. Variable ordering for the orthogonalized IRFs: credit cycle (CR), housing cycle (H), bond cycle (B), equity cycle (EQ). Dashed lines show the 95% confidence bands. Impulse and response variables are indicated above each subfigure.

(a) Gaps



(b) First differences

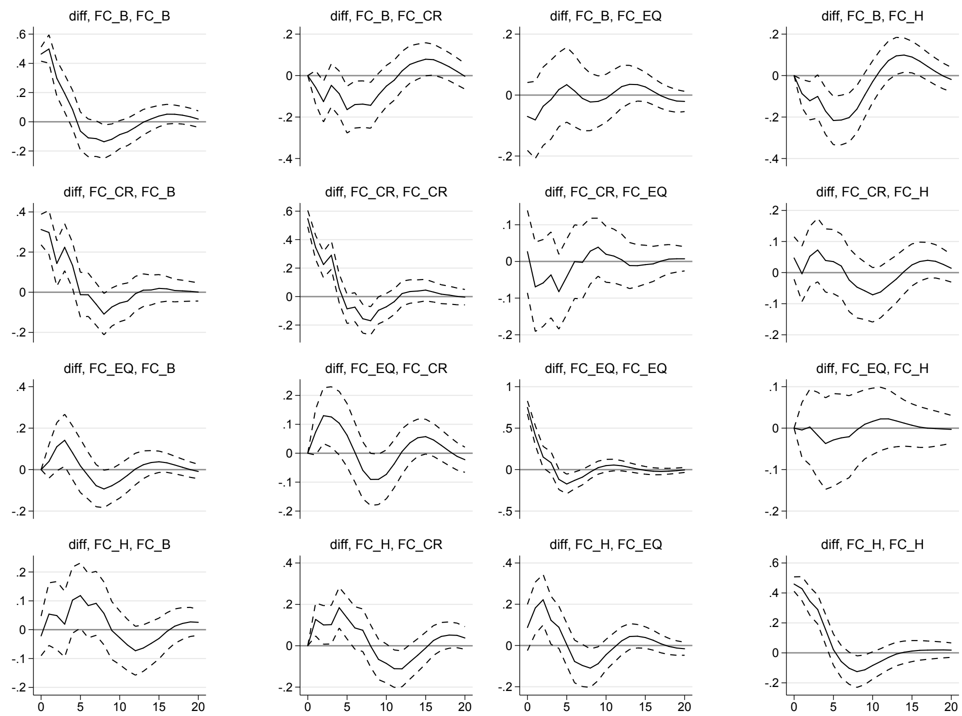


Figure 11: Credit financial cycles: GBR

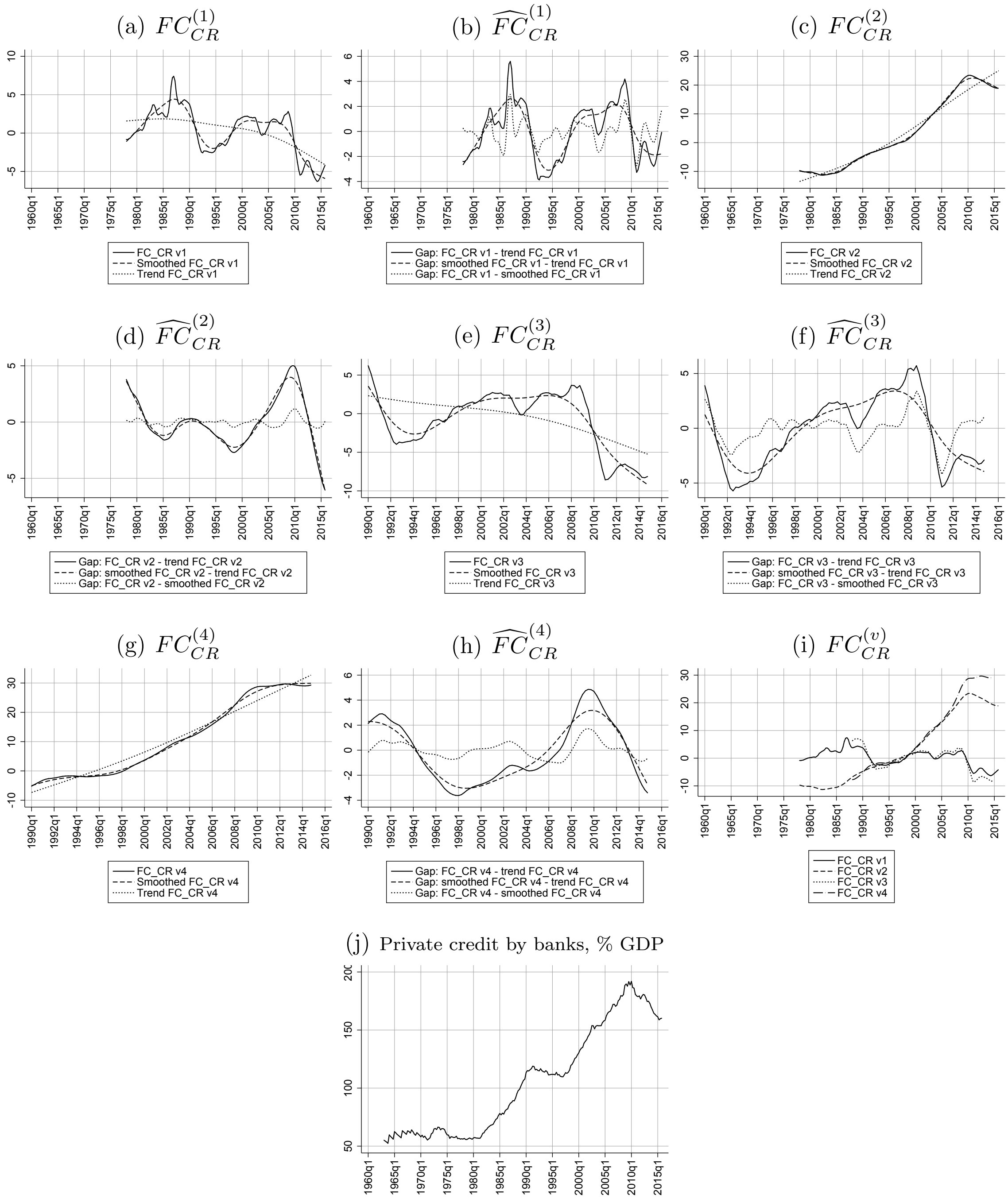
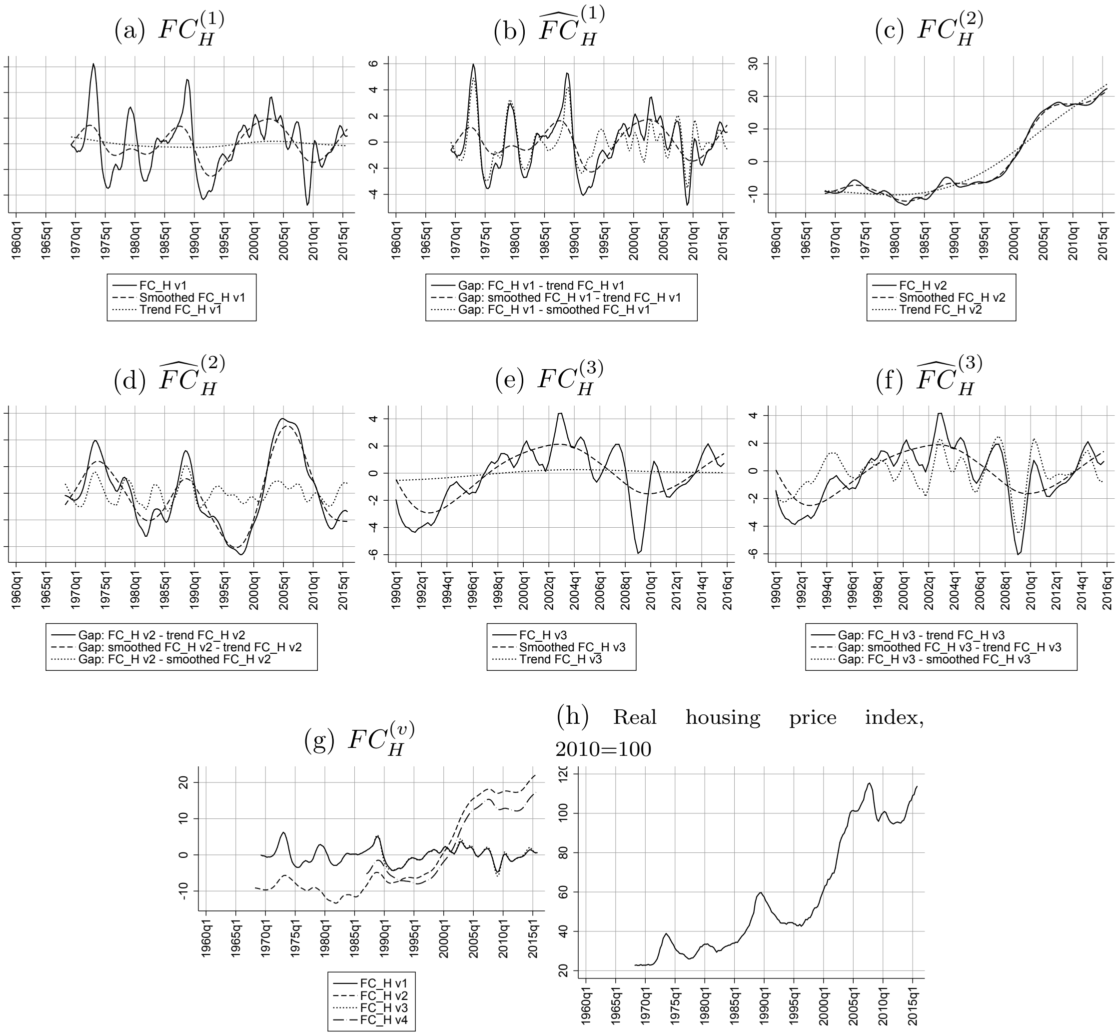


Figure 12: Housing financial cycles: GBR



(a) $FC_H^{(1)}$ (b) $\widehat{FC}_H^{(1)}$ (c) $FC_H^{(2)}$

(d) $\widehat{FC}_H^{(2)}$ (e) $FC_H^{(3)}$ (f) $\widehat{FC}_H^{(3)}$

(g) $FC_H^{(v)}$ (h) Real housing price index, 2010=100

Figure 13: Bond financial cycles: GBR

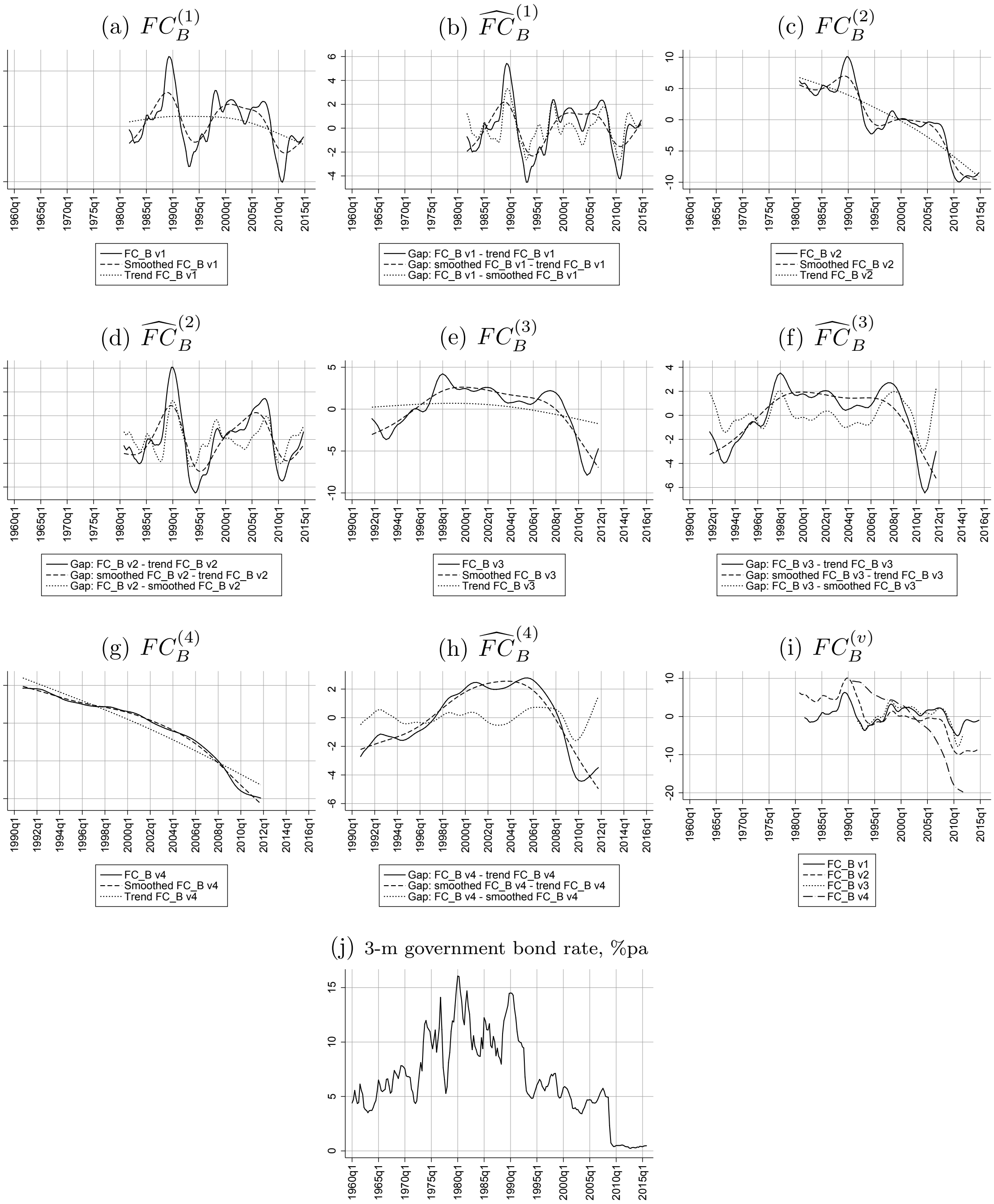
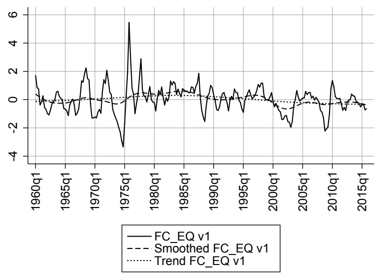
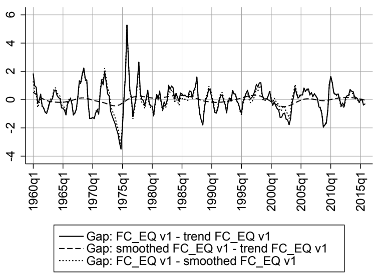


Figure 14: Equity financial cycles: GBR

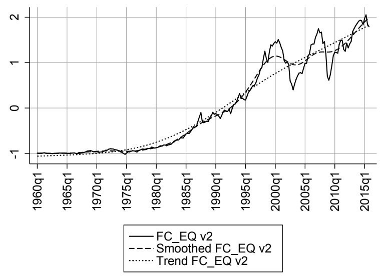
(a) $FC_{EQ}^{(1)}$



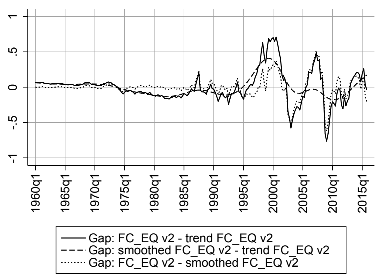
(b) $\widehat{FC}_{EQ}^{(1)}$



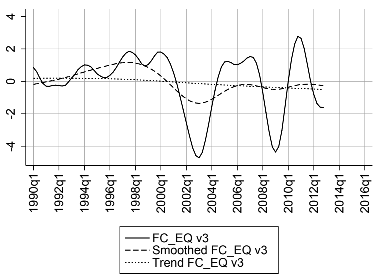
(c) $FC_{EQ}^{(2)}$



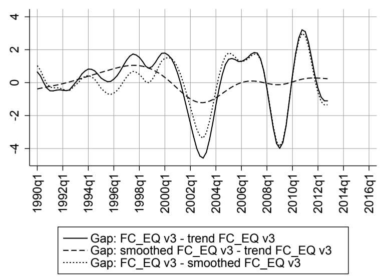
(d) $\widehat{FC}_{EQ}^{(2)}$



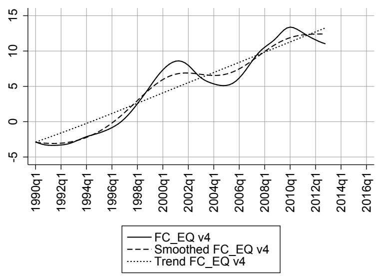
(e) $FC_{EQ}^{(3)}$



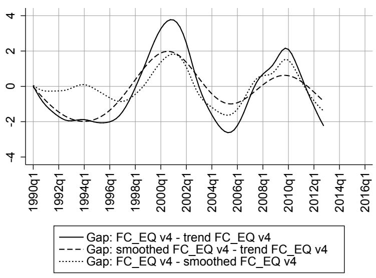
(f) $\widehat{FC}_{EQ}^{(3)}$



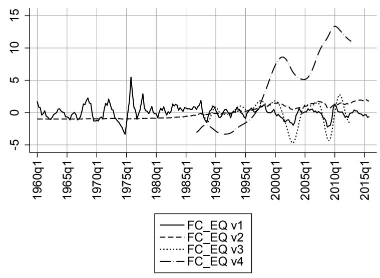
(g) $FC_{EQ}^{(4)}$



(h) $\widehat{FC}_{EQ}^{(4)}$



(i) $FC_{EQ}^{(v)}$



(j) Stock market index, FTSE

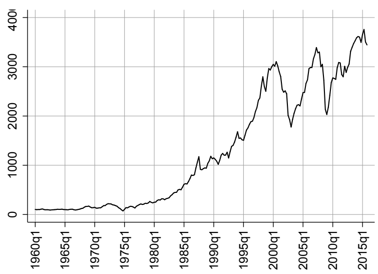


Figure 15: Aggregate financial cycles: GBR

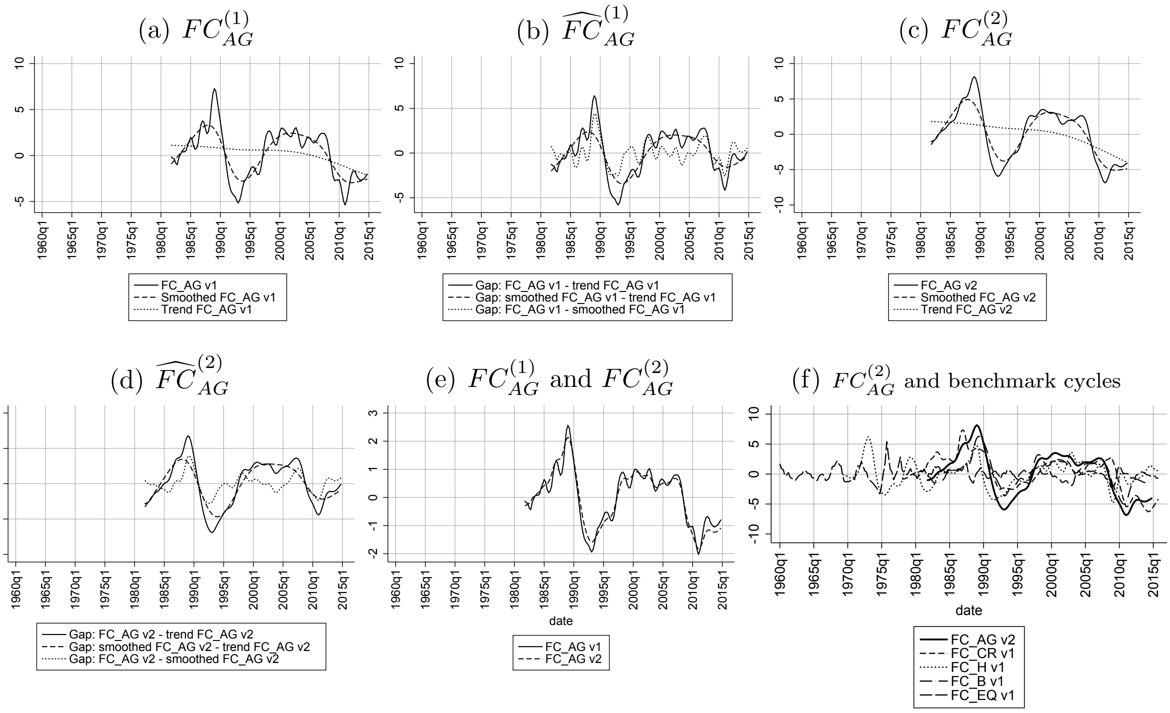


Figure 16: Scatterplot matrix of main financial cycles: GBR

Notes: The figure shows scatterplots of the benchmark segment-specific (CR, H, B, EQ) and aggregate (AG) financial cycles in levels and first differences (D).

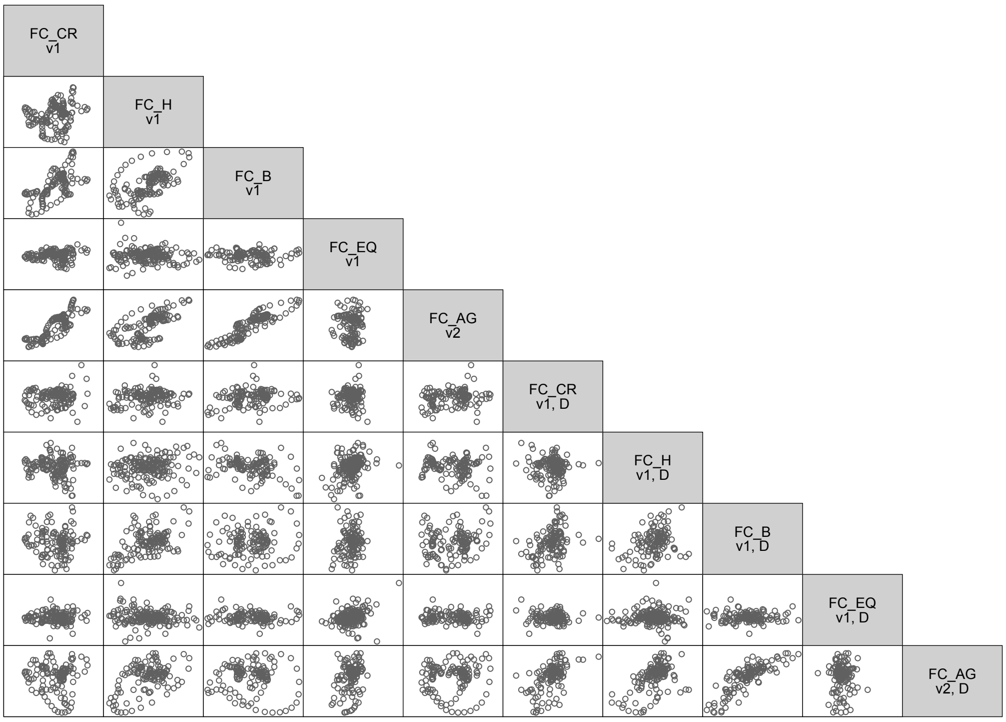
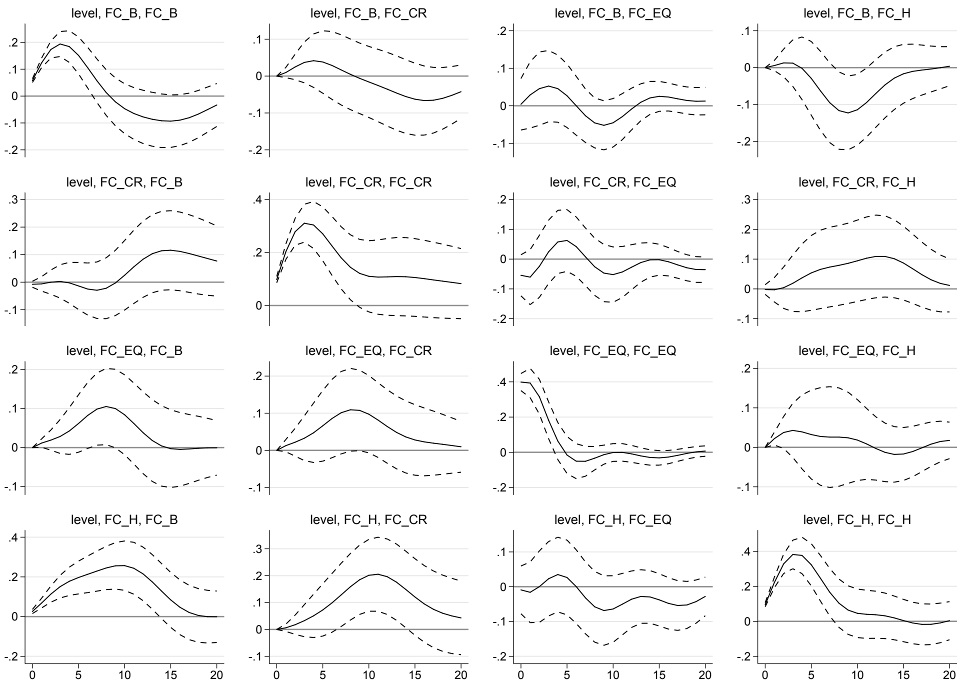


Figure 17: Impulse-response functions: GBR

Notes: VAR(K) lag order based on conventional (Akaike, Hannan-Quinn, Schwarz Bayesian) information criteria: $K = 3$ for Model (a)—in gaps (deviations from the trend); $K = 2$ for Model (b)—in first differences. Variable ordering for the orthogonalized IRFs: credit cycle (CR), housing cycle (H), bond cycle (B), equity cycle (EQ). Dashed lines show the 95% confidence bands. Impulse and response variables are indicated above each subfigure.

(a) Gaps



(b) First differences

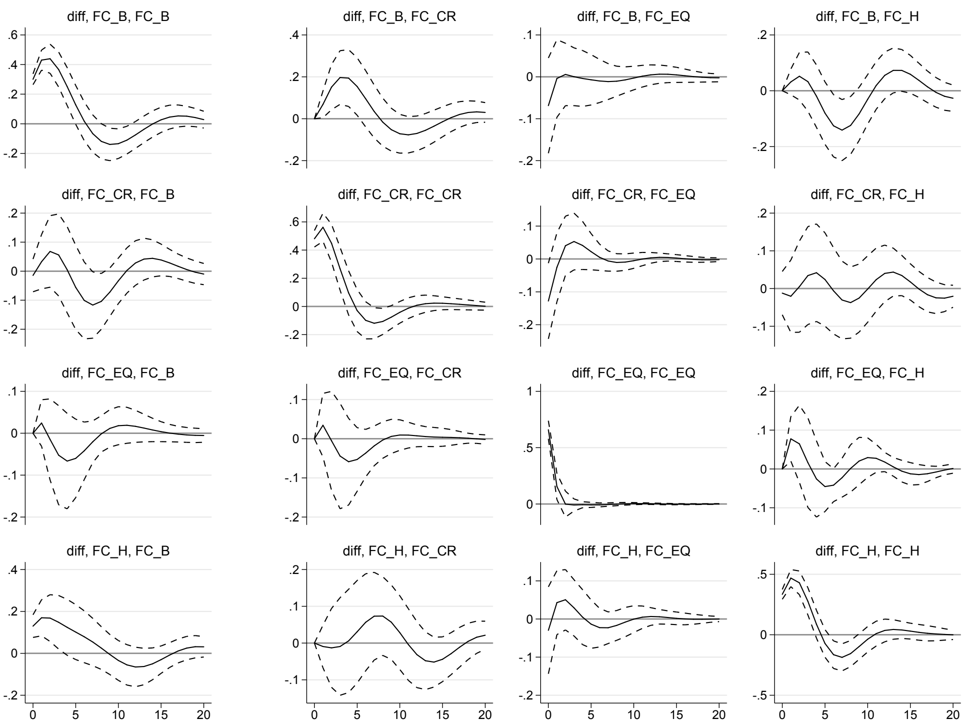


Figure 18: Credit financial cycles: DEU

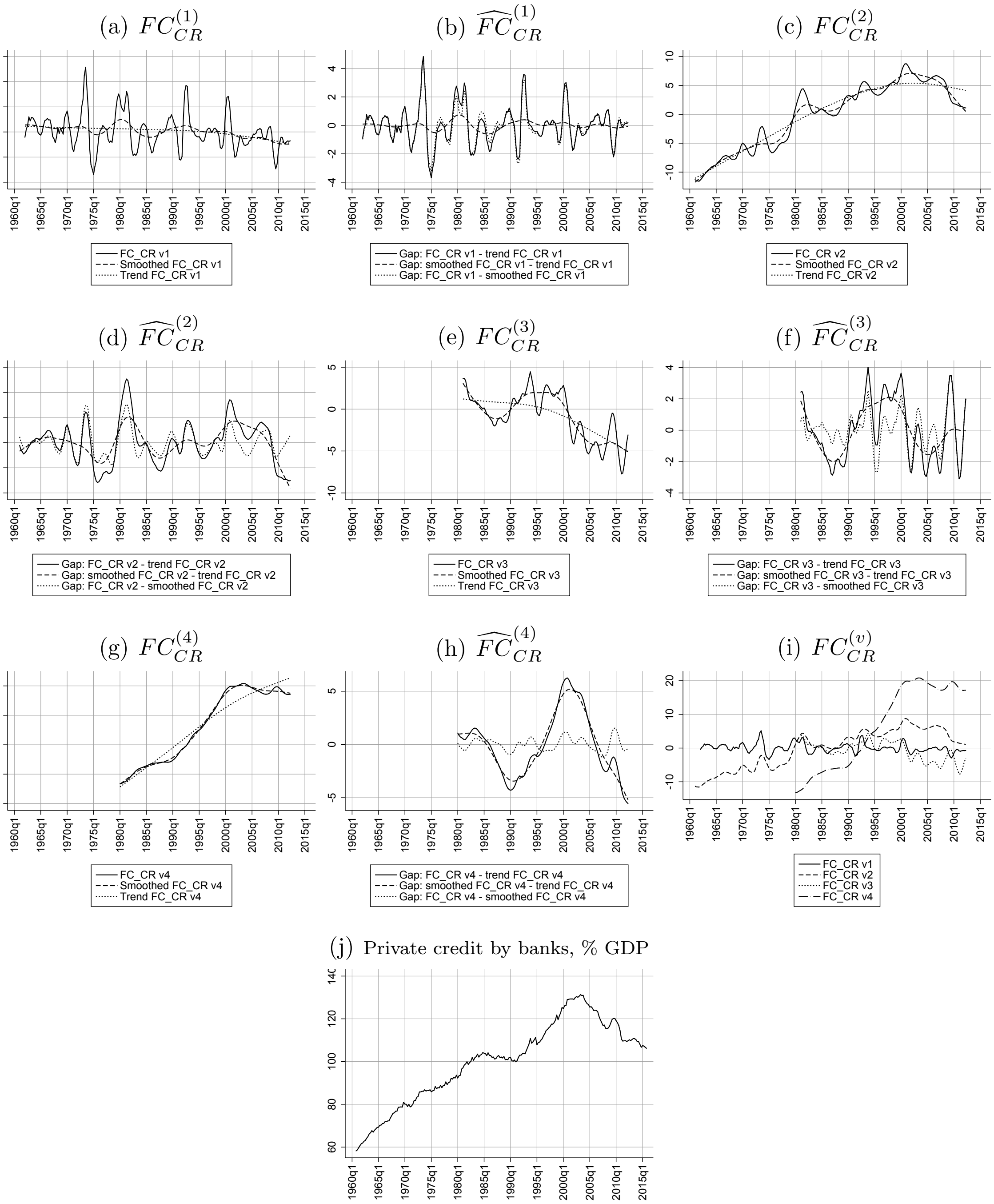
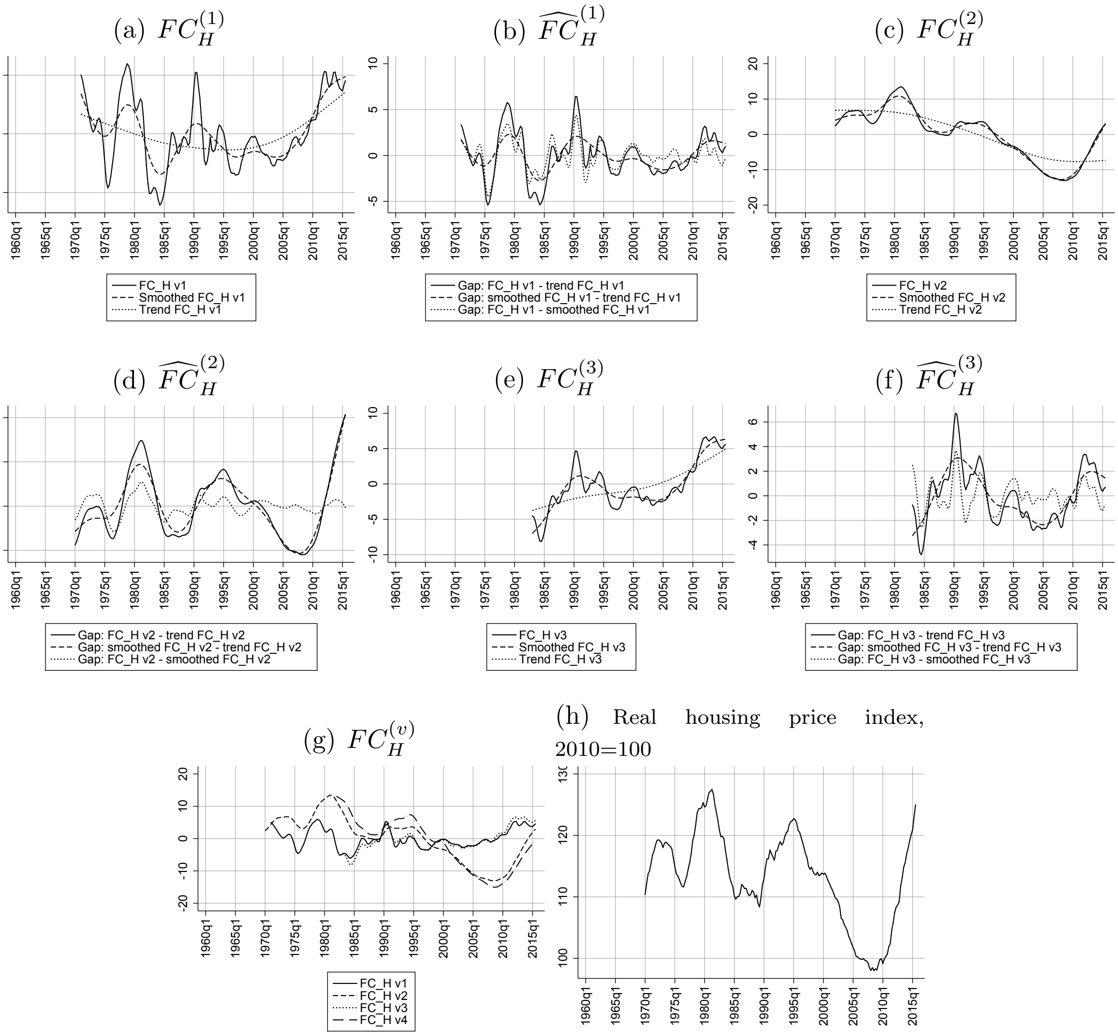


Figure 19: Housing financial cycles: DEU



(a) $FC_H^{(1)}$ (b) $\widehat{FC}_H^{(1)}$ (c) $FC_H^{(2)}$

(d) $\widehat{FC}_H^{(2)}$ (e) $FC_H^{(3)}$ (f) $\widehat{FC}_H^{(3)}$

(g) $FC_H^{(v)}$ (h) Real housing price index, 2010=100

Figure 20: Bond financial cycles: DEU

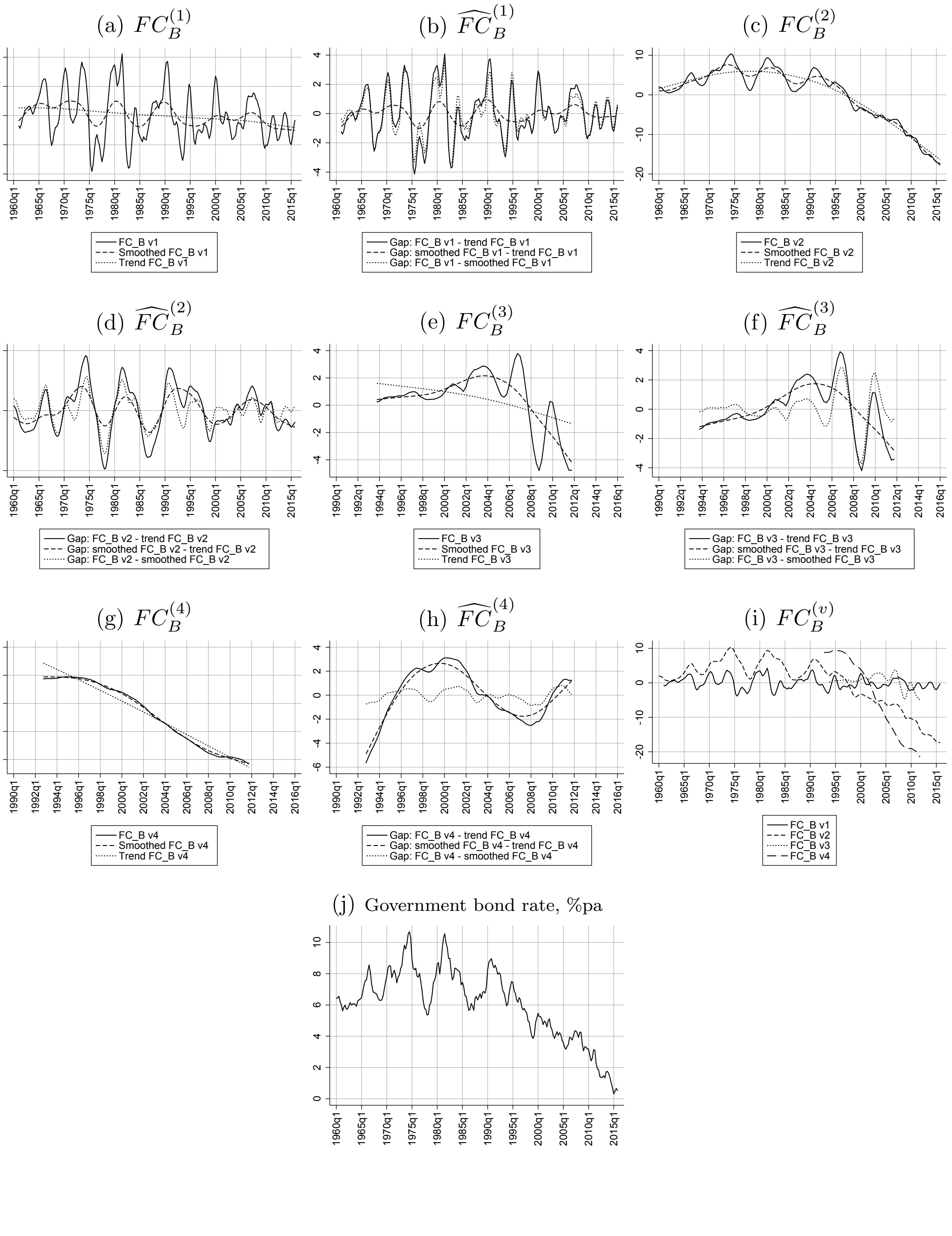


Figure 21: Equity financial cycles: DEU

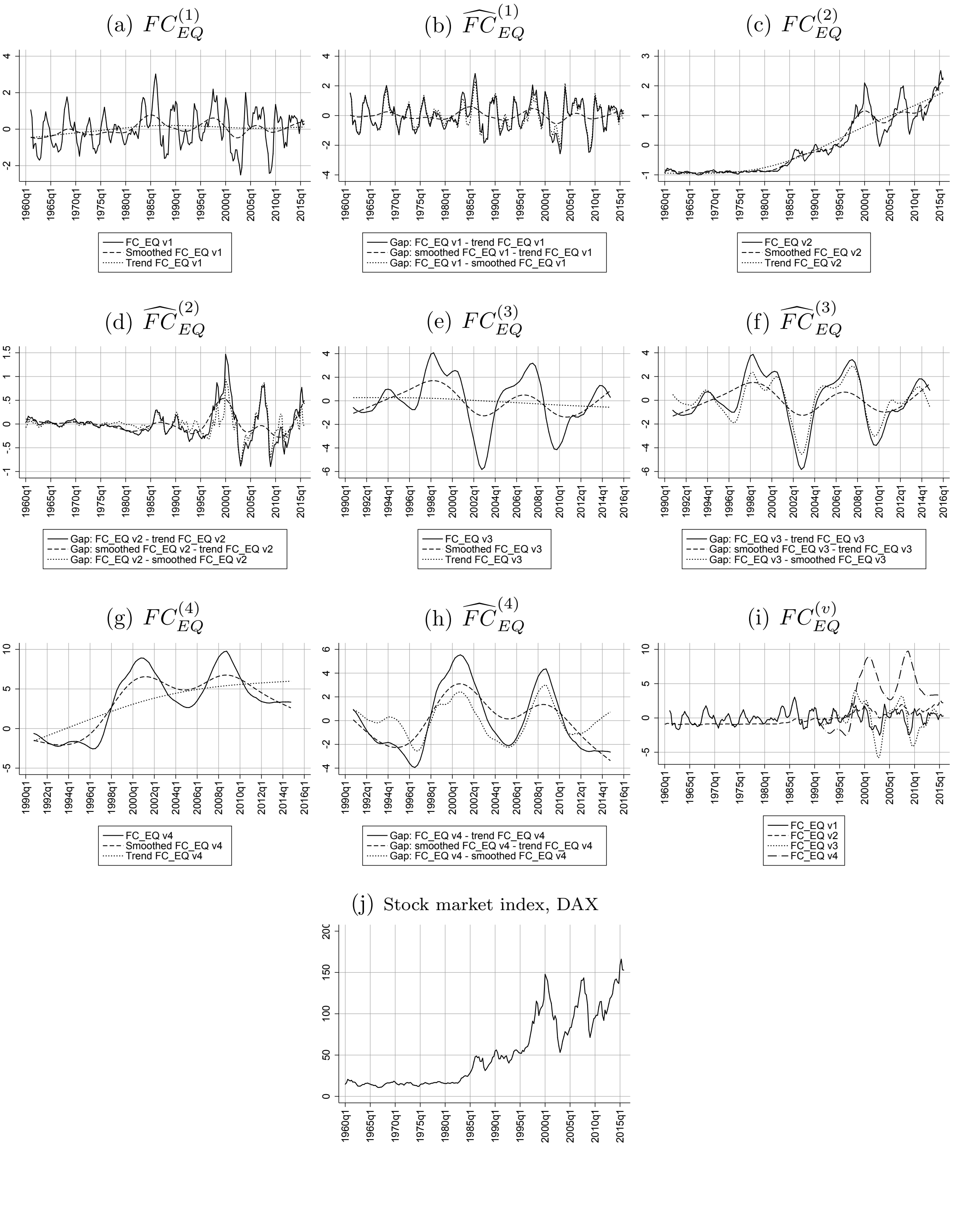


Figure 22: Aggregate financial cycles: DEU

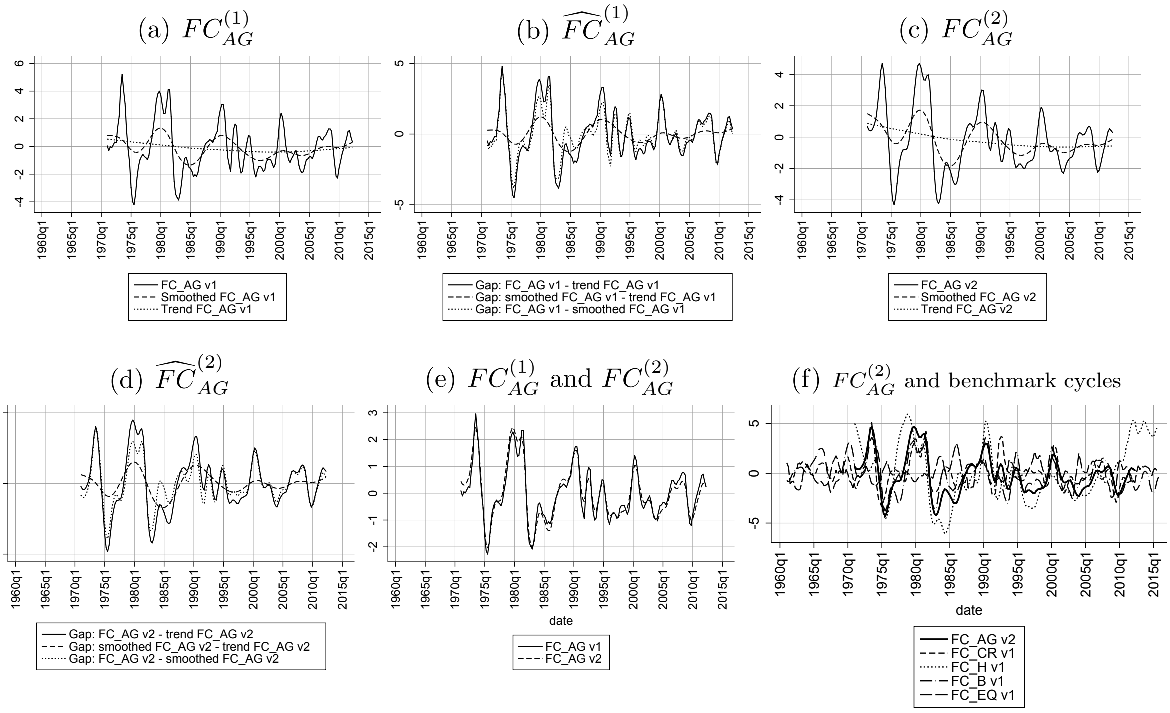


Figure 23: Scatterplot matrix of main financial cycles: DEU

Notes: The figure shows scatterplots of the benchmark segment-specific (CR, H, B, EQ) and aggregate (AG) financial cycles in levels and first differences (D).

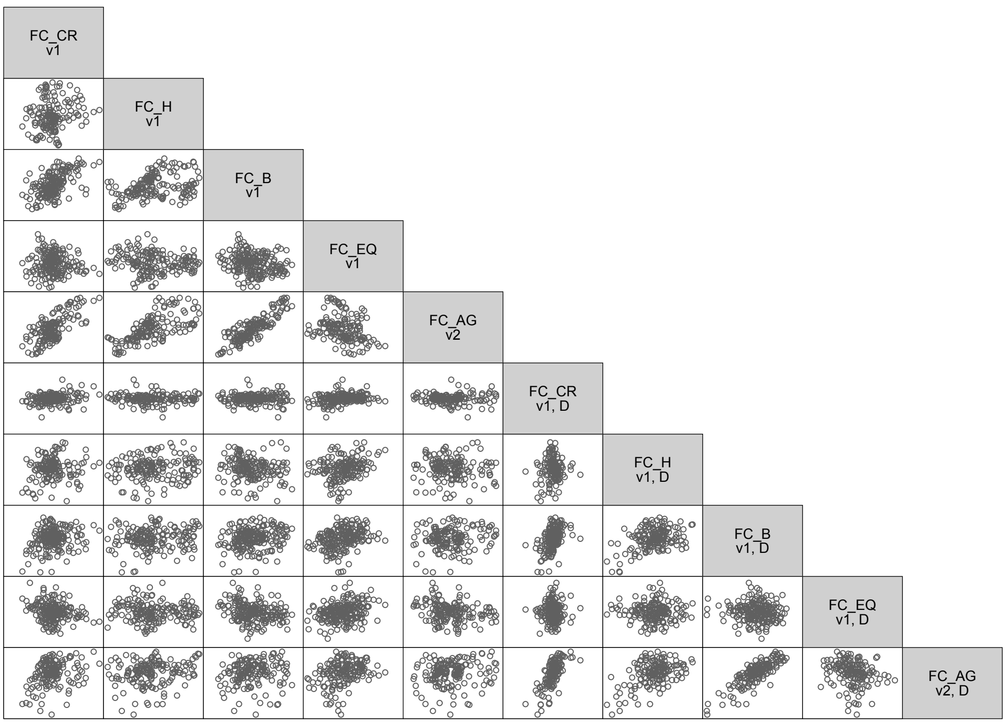
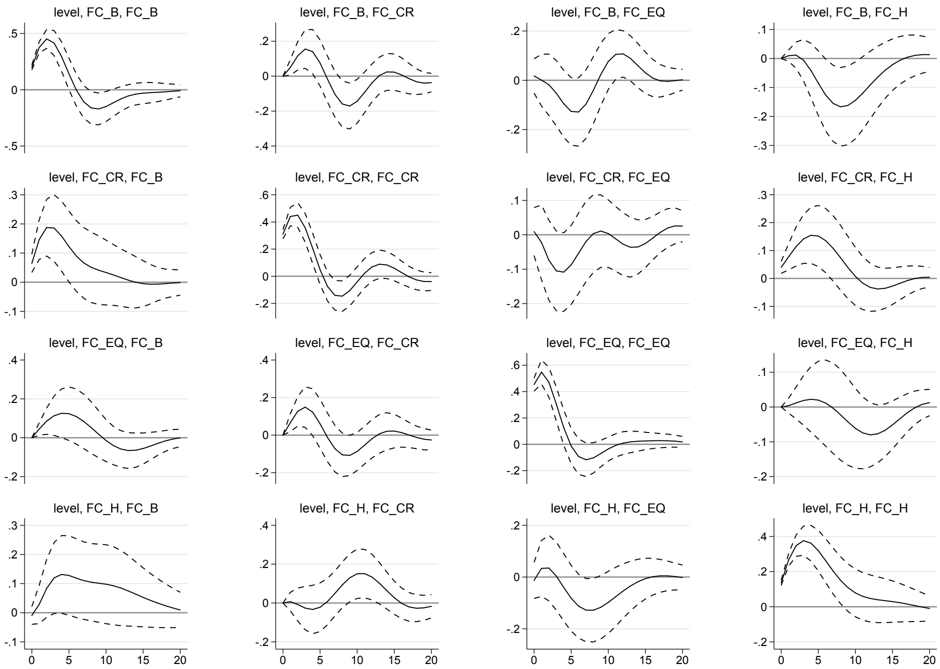


Figure 24: Impulse-response functions: DEU

Notes: VAR(K) lag order based on conventional (Akaike, Hannan-Quinn, Schwarz Bayesian) information criteria: $K = 3$ for Model (a)—in gaps (deviations from the trend); $K = 2$ for Model (b)—in first differences. Variable ordering for the orthogonalized IRFs: credit cycle (CR), housing cycle (H), bond cycle (B), equity cycle (EQ). Dashed lines show the 95% confidence bands. Impulse and response variables are indicated above each subfigure.

(a) Gaps



(b) First differences

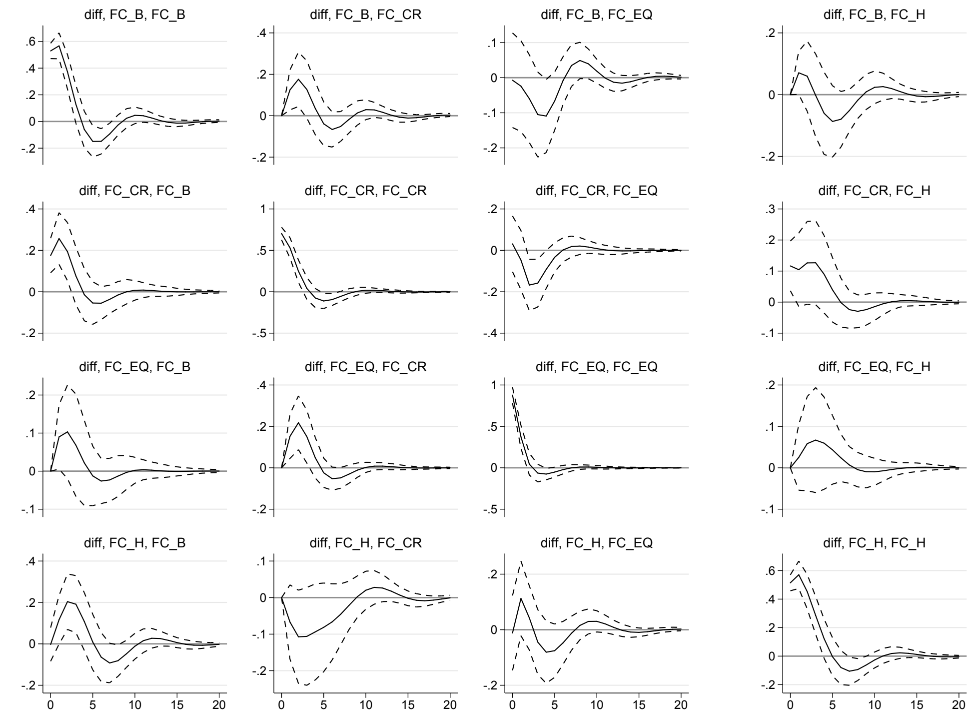


Figure 25: Credit financial cycles: JPN

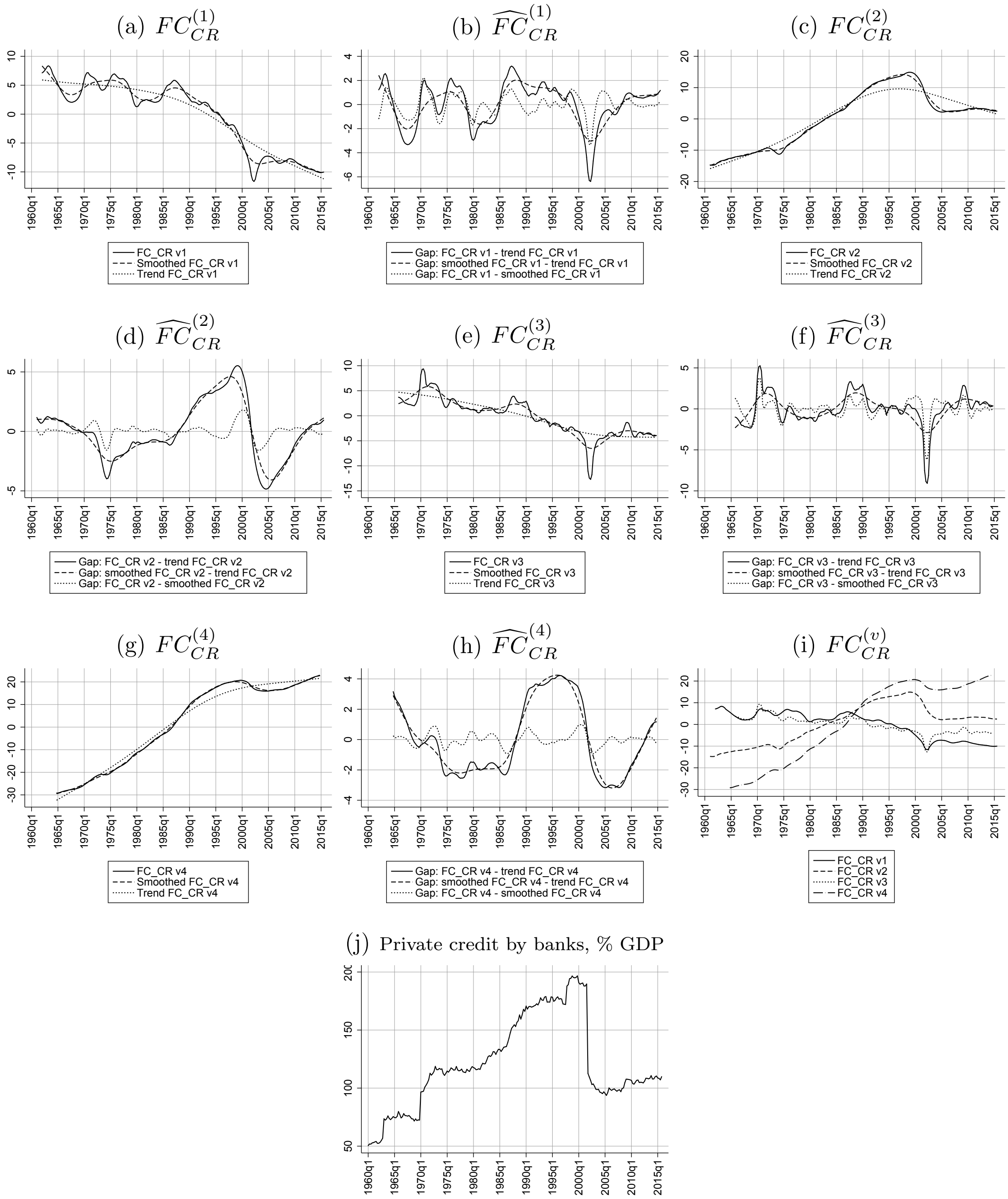


Figure 26: Housing financial cycles: JPN

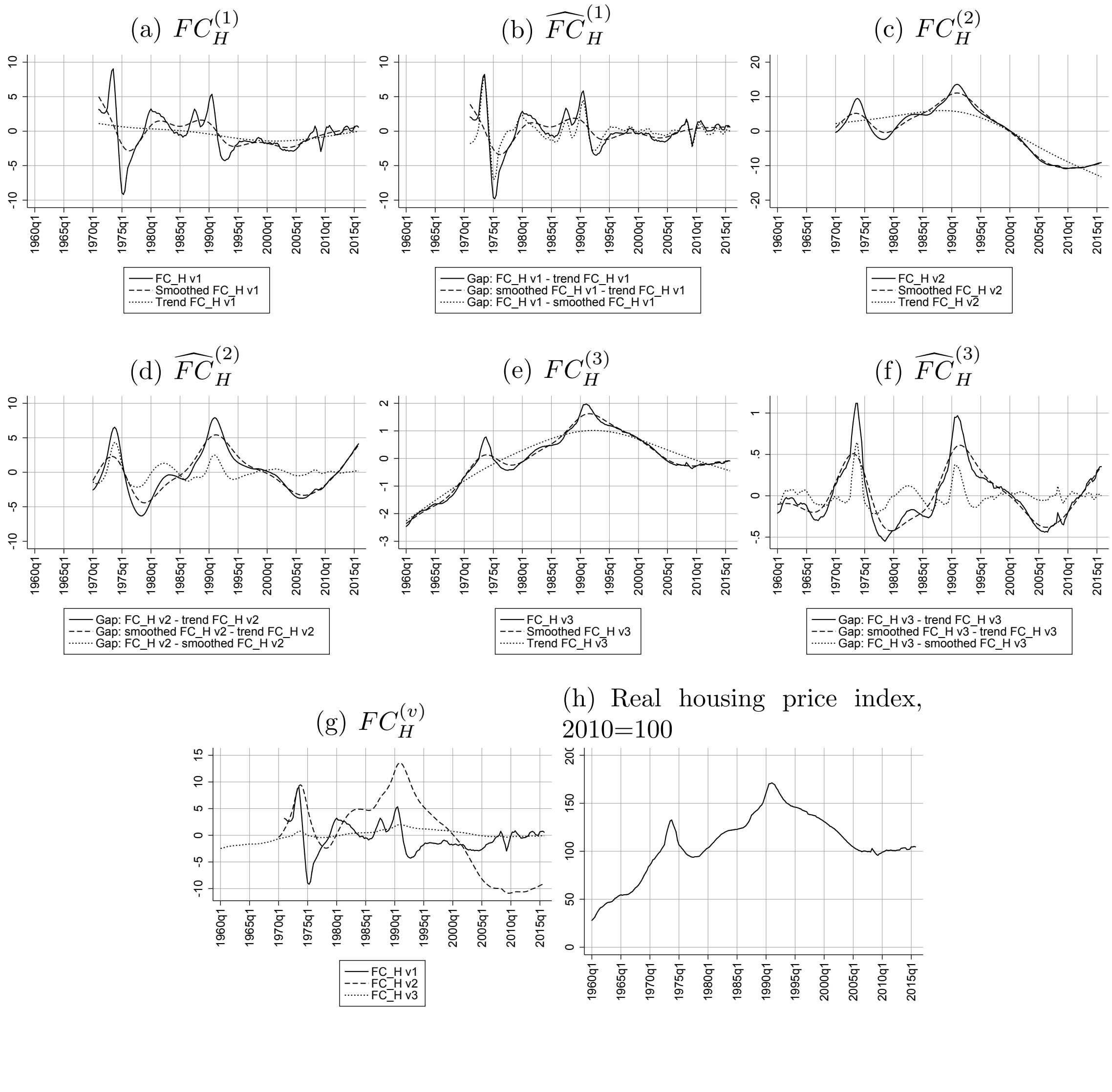


Figure 27: Bond financial cycles: JPN

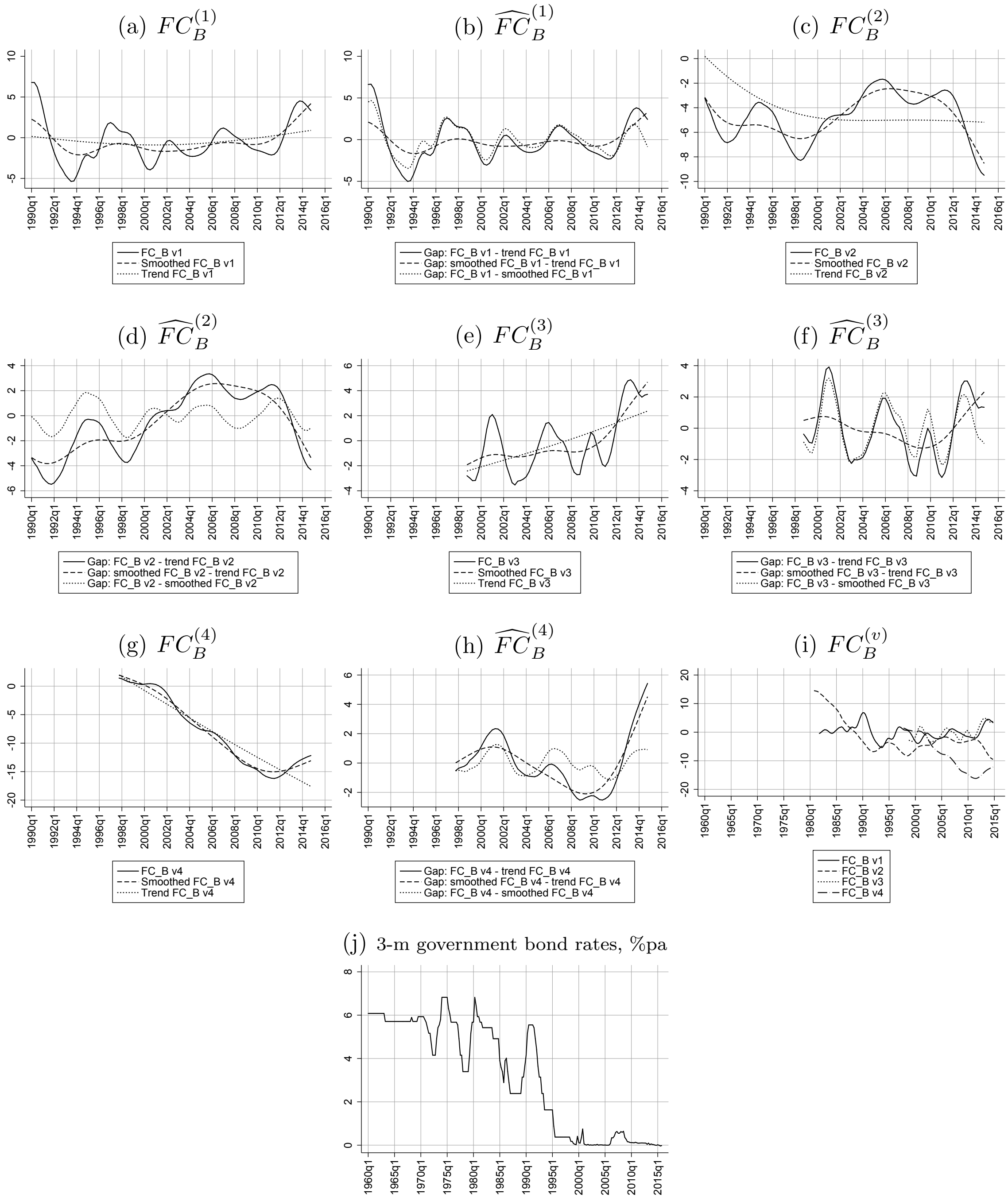


Figure 28: Equity financial cycles: JPN

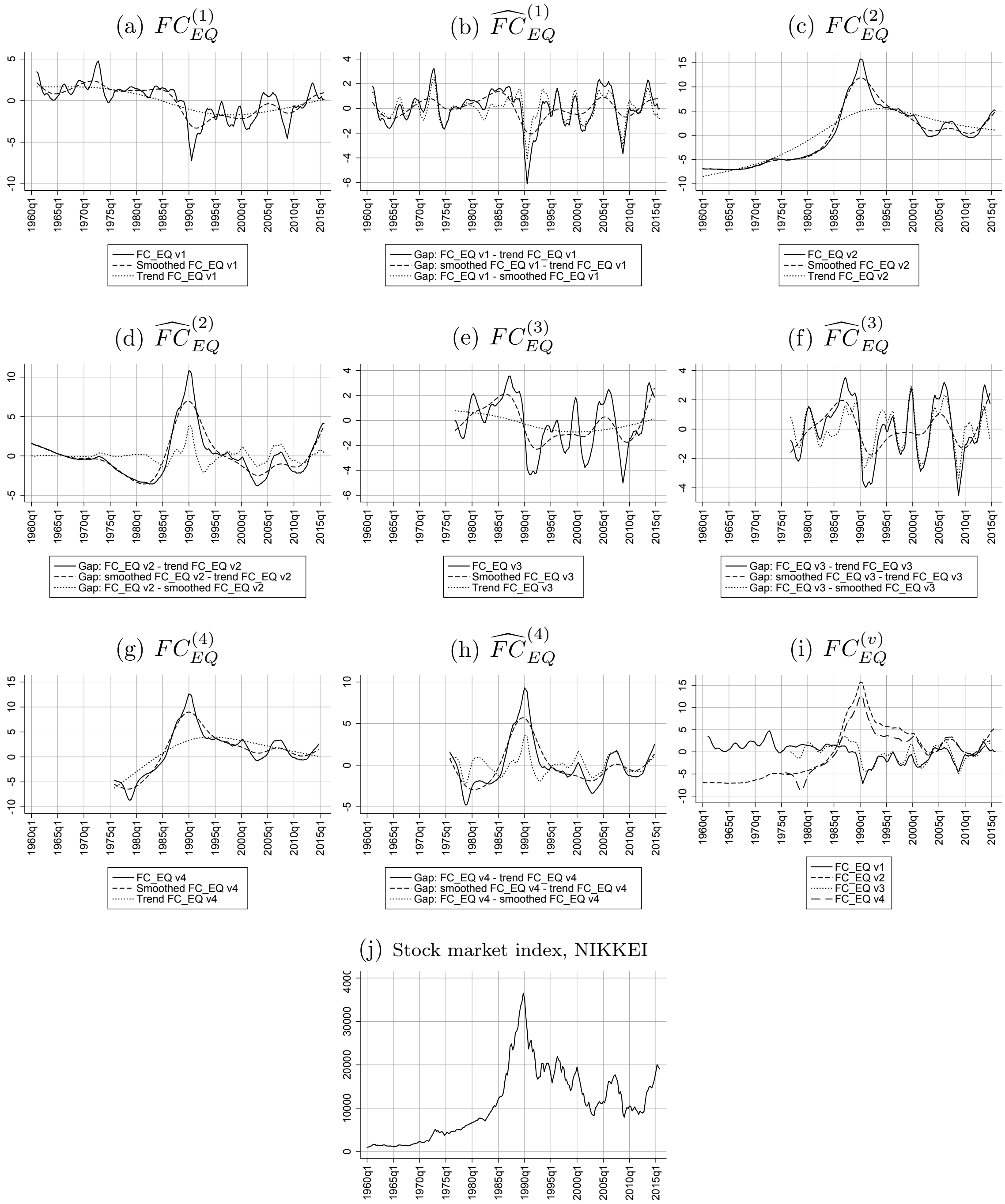
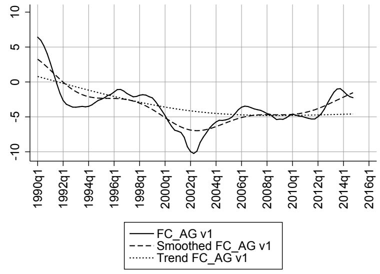
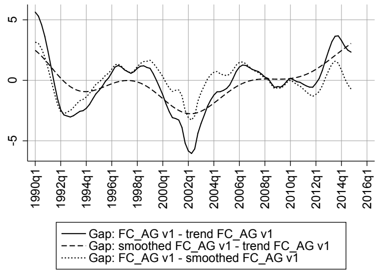


Figure 29: Aggregate financial cycles: JPN

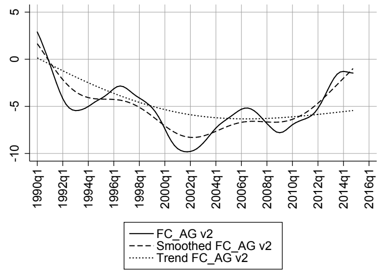
(a) $FC_{AG}^{(1)}$



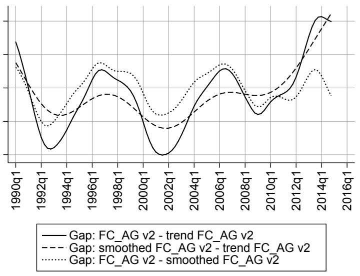
(b) $\widehat{FC}_{AG}^{(1)}$



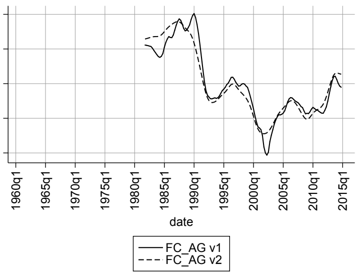
(c) $FC_{AG}^{(2)}$



(d) $\widehat{FC}_{AG}^{(2)}$



(e) $FC_{AG}^{(1)}$ and $FC_{AG}^{(2)}$



(f) $FC_{AG}^{(2)}$ and benchmark cycles

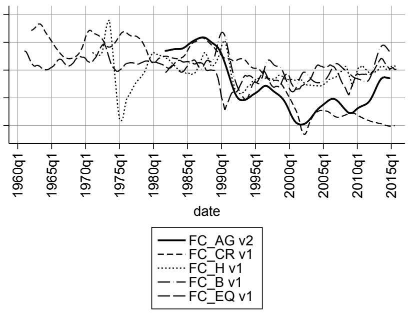


Figure 30: Scatterplot matrix of main financial cycles: JPN

Notes: The figure shows scatterplots of the benchmark segment-specific (CR, H, B, EQ) and aggregate (AG) financial cycles in levels and first differences (D).

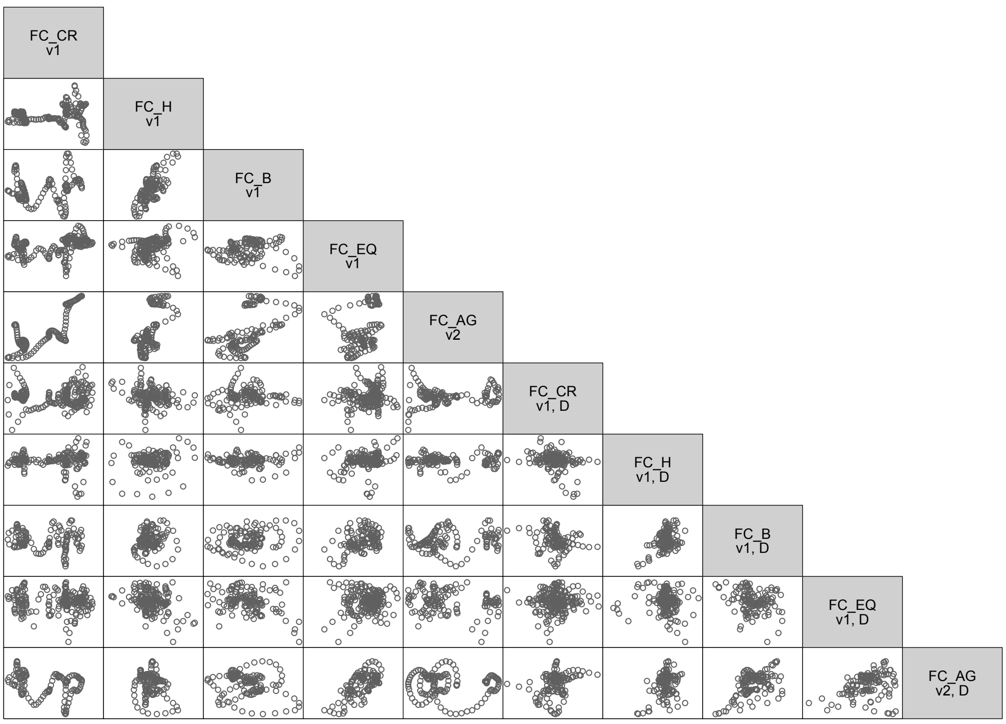
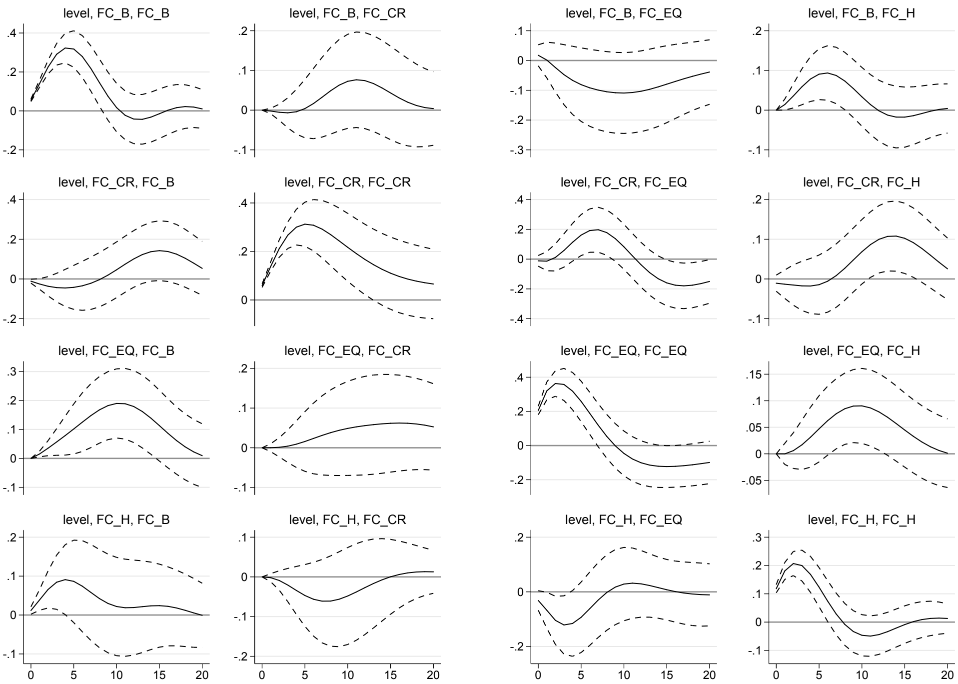


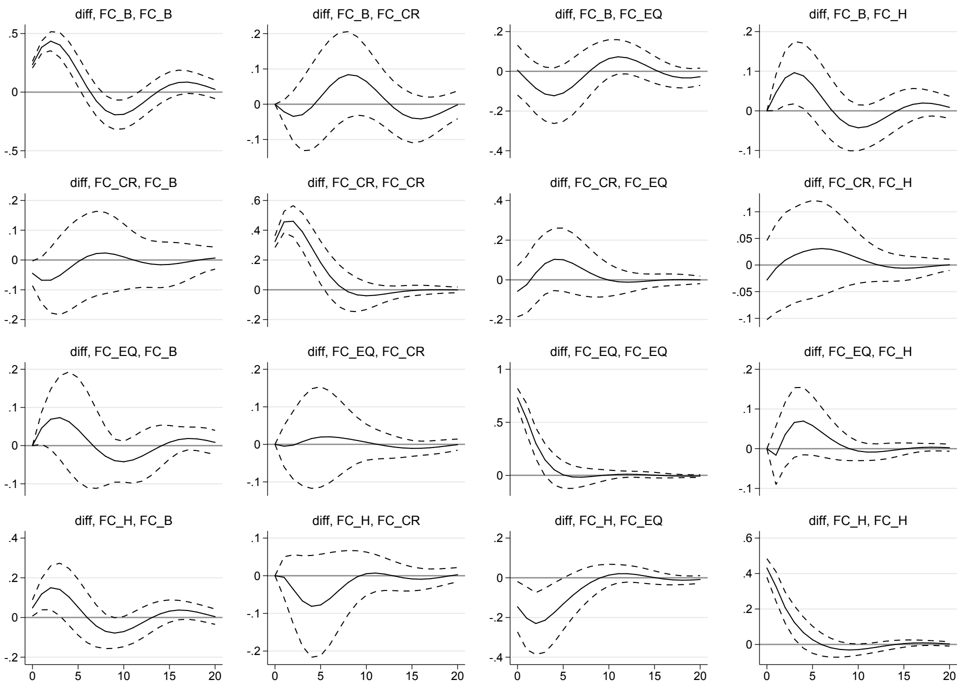
Figure 31: Impulse-response functions: JPN

Notes: VAR(K) lag order based on conventional (Akaike, Hannan-Quinn, Schwarz Bayesian) information criteria: $K = 3$ for Model (a)—in gaps (deviations from the trend); $K = 2$ for Model (b)—in first differences. Variable ordering for the orthogonalized IRFs: credit cycle (CR), housing cycle (H), bond cycle (B), equity cycle (EQ). Dashed lines show the 95% confidence bands. Impulse and response variables are indicated above each subfigure.

(a) Gaps



(b) First differences



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