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ARTICLE

Macro-financial imbalances and cyclical systemic risk dynamics: understanding the factors driving the financial cycle in the presence of non-linearities

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Abstract

This paper develops a multivariate filter based on an unobserved component model to estimate the financial cycle. Our model features: (1) a dynamic relationship between the financial cycle and key variables; (2) time-varying shock volatility for trend and cycle components. We demonstrate that our approach not only exhibits superior early warning properties for banking crises but also outperforms commonly used indicators in terms of data fit for decomposition exercises, as evidenced by the higher marginal likelihood. We document three important properties of the financial cycle. First, the sensitivity of the financial cycle to changes in real estate valuations increased during the post-90s period. Second, the sensitivity of the cycle to changes in financial conditions displays volatility and country specificities. Finally, our reduced form estimates suggest that the banking crisis of 1988 was preceded by positive contributions from the risk appetite shock, while the primary source of vulnerabilities emanated from the housing market in the run-up to the Global Financial Crisis.

Keywords: Cyclical systemic risk; financial cycle; multivariate unobserved component models; stochastic volatility

1. Introduction

Reliable measurement of the financial cycle plays a critical role in the conduct of countercyclical macroprudential policy.[1] Established indicators of the financial cycle, such as the Basel-gap, employ the one-sided Hodrick and Prescott (1997) low-pass filter (HP-filter) or bandpass filters to isolate medium-term frequencies in the credit-to-GDP ratio.[2] In contrast to model-based filters, statistical filters do not require a definition of the parametric structure of the trend-cycle components, but just need that the frequency is specified upfront.

Given their ease of application, frequency-based non-parametric filters have proven popular. However, the application of the HP-filter to difference-stationary time series can lead to the emergence of spurious cycles. In such cases, the duration of boom and bust phases lacks a basis in the underlying series (see Cogley and Nason (1995) and Hamilton (2018)). Furthermore, in cases where financial crises occur at shorter intervals than suggested by the chosen frequency, the indicator may fail to signal excessive developments (e.g. Schüler (2020)). The identified limitations may constrain the ability of policymakers to discern and respond to the development of macro-financial vulnerabilities (e.g. Hamilton and Leff (2020) or Schüler et al. (2020)). To overcome the shortcomings of frequency-based non-parametric filters and address the lack of an accurate measure, this paper presents estimates of the financial cycle based on a filter that (1) synthesizes coincident multivariate dynamics to inform the estimation of the cycle of key economic and financial variables, (2) stipulates a time-varying law of motion for the uncertainty in the trend and the cycle, and (3) is agnostic about the frequency specification. Specifically, the relationship between the cyclical factors driving the credit ratio and auxiliary variables is explicitly described by a set of equations that form a multivariate unobserved component model. We show that our filter is able to capture cyclical movements more accurately than indicators of the financial cycle that are well-established in the policy field and rely on similar-duration assumptions.

Uncertainty in the observed and unobserved components that form the state space evolves following a stochastic volatility process.[3] This is an advance relative to homoskedastic approaches to estimate the financial cycle, since those do not account for non-linear dynamics in the interrelation between the financial system and the macroeconomy.[4] The constant variance specification of previous methods may lead to exaggerated dynamics in the estimated cyclical component, if it captures the movements in volatility that are not modeled. Another significant advantage of the heteroskedastic variance structure is the exploration of time-varying Kalman gains, enabling the sensitivity of the unobserved components to evolve dynamically in response to signals from the observable variables.

Our aim is to contribute to the stream of literature that has put forward methods that improve the estimation of the financial cycle, in particular those that explicitly model the cycle.[5] Estimating the financial cycle as a deviation from equilibrium credit, modeled within a univariate trend-cycle equation, and the synthesis of coincident multivariate dynamics to inform the estimation of the cycle is shared with earlier studies. However, the combination of both together with an heteroskedastic error structure is, to the best of our knowledge, new.

Results from both a Monte Carlo experiment and empirical application illustrate that our decomposition method is favored by the data and demonstrates a more timely detection of the buildup of systemic crises compared to existing indicators commonly used by policymakers. Additionally, we find heterogeneity in the role of the factors driving the financial cycle that preceded the banking crises covered in our data sample. In particular, changes in the financial conditions increased macro-financial vulnerabilities in the period prior to the "Savings and Loans Crisis" (SLC), while changes in household vulnerabilities were the main driving factor in the years prior to the "Global Financial Crisis" (GFC).

The paper is organized as follows: Section 2 introduces the empirical model and provides details on the estimation method. Section 3 contains the results of a small Monte Carlo experiment with simulated data. The results from the empirical model are presented in Section 4. Section 5 provides conclusions.

2. Empirical model

This section describes the structure of the decomposition model, the dynamics of the trend and the cycle components and the estimation procedure. A key motivator for the empirical approach is that macro-financial dynamics, and more specifically the concept of the financial cycle as relevant for policymakers, are characterized by the cyclical joint behavior of credit, asset prices and macroeconomic aggregates. We operationalize this notion by informing the estimation of the cycle through auxiliary variables. In addition, time variation is introduced into the model by allowing for a drift in the error covariance matrix of the transition equation.

2.1. Unobserved components model of trend-cycle decomposition

We postulate that the target variable Θ_t will be decomposed into a stochastic trend τ_t and a stationary component c_t.

$$\boldsymbol{\Theta}_t = \tau_t + c_t \tag{1}$$

Consistent with Beveridge and Nelson (1981), the trend is defined as the expectation of values of Θ_t at the infinite horizon, conditional on a set of currently available information Ξ_t.

$$E\left(\Theta_{t+\infty}|\,\Xi_t\right) = \tau_t \tag{2}$$

As noted in Mertens (2016), identifying the trend as an expectation carries the assumption that first-differencing (2) generates a unit root process for the trend, in which the trend disturbances e_t^{τ} build a martingale-difference sequence.

$$\tau_t = \tau_{t-1} + E\left(\Theta_{t+\infty}|\,\Xi_t\right) - E\left(\Theta_{t+\infty}|\,\Xi_{t-1}\right) = \tau_{t-1} + e_t^{\tau} \tag{3}$$

Hence, the trend τ_t evolves as a random walk. In our specification the local disturbance of the trend evolves with stochastic volatility.

$$\tau_t = \tau_{t-1} + \upsilon_t\sqrt{exp(ln\lambda_t)}, \quad \upsilon_t \sim N(0, 1) \tag{4}$$

$$ln(\lambda_t) = ln(\lambda_{t-1}) + \rho_t, \quad \rho_t \sim N(0, \sigma_\rho) \tag{5}$$

The cyclical component c_t displays the stationary variation within the time series, $E(c_t) = 0$.[6] Building on the notion that the cyclical dimension of systemic risk is described by the common variation of relevant indicators, a number of auxiliary variables will contribute to its identification. A Bayesian vector autoregression (BVAR) with stochastic volatility captures the joint dynamics between the cycle and the auxiliary variables.

The BVAR(p) with stochastic volatility follows an autoregressive process of order p and takes the form:

$$Z_t = F_tB + \nu_t, \quad \nu_t = A^{-1}\Lambda_t^{0.5}\epsilon_t, \quad \epsilon_t \sim N(0, I_N), \quad \Lambda_t = diag(\lambda_{1,t}, \ldots, \lambda_{N,t}) \tag{6}$$

$$ln(\lambda_{i,t}) = ln(\lambda_{i,t-1}) + \omega_{i,t}, \quad \omega_{i,t} \sim N(0, \sigma_\omega) \tag{7}$$

where $Z_t = (c_t, AX_{1t}, \ldots, AX_{kt})'$ is a matrix of endogenous variables (for $i = 1, \ldots, N$ model variables of which $k = 1, \ldots, K$ are auxiliary variables). $F_t = (Z'_{t-1}, \ldots, Z'_{t-p}, 1)'$ denotes the matrix of regressors and B is the matrix of coefficients $B = (B_1, \ldots, B_P, \mu)'$. $\mu = (\mu_1, \ldots, \mu_n)'$ is an N-dimensional vector of constants and $B_1, \ldots, B_P$ are NxN autoregressive matrices.

A is a lower triangular matrix with ones on the main diagonal and coefficients α_{qj} in row q and column j (for $q = 2, \ldots, N, j = 1, \ldots, i-1$) and Λ_t is a diagonal matrix which contains the stochastic volatilities. As in equation (5) these evolve as geometric driftless random walks. The vector of innovations to volatilities ϵ_t is independent across time, with a variance matrix that is diagonal following Cogley and Sargent (2005). Given that Primiceri (2005) found little variation in the elements in A^{-1} and it would require the estimation of additional $N(N-1)/2$ equations, we don't allow the elements in A^{-1} to vary over time.[7]

The reduced form VAR innovation ν_t time-varying covariance matrix is factored as

$$VAR(\nu_t) \equiv \Sigma_t = A^{-1}\Lambda_t(A^{-1})' \tag{8}$$

Our multivariate filter for trend-cycle decomposition can be compactly written in state space form. It is a combination of the law of motion for the trend and the dynamics for the cycle. The transition equation describes the dynamics within the state space, taking as an example the case $k = 2$.

$$\begin{bmatrix} \tau_t \\ c_t \\ AX_{1t} \\ AX_{2t} \\ c_{t-1} \\ AX_{1t-1} \\ AX_{2t-1} \end{bmatrix} = \begin{bmatrix} 0 \\ \mu_1 \\ \mu_2 \\ \mu_3 \\ 0 \\ \vdots \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & \cdots & \cdots & \cdots & \vdots \\ 0 & b_{11} & b_{12} & b_{13} & b_{14} & b_{15} & b_{16} \\ \vdots & b_{21} & b_{22} & b_{23} & b_{24} & b_{25} & b_{26} \\ \vdots & b_{31} & b_{32} & b_{33} & b_{34} & b_{35} & b_{36} \\ \vdots & 1 & 0 & \cdots & \cdots & \cdots & \vdots \\ \vdots & 0 & 1 & 0 & \cdots & \cdots & \vdots \\ 0 & \cdots & \cdots & 1 & 0 & \cdots & 0 \end{bmatrix} \begin{bmatrix} \tau_{t-1} \\ c_{t-1} \\ AX_{1t-1} \\ AX_{2t-1} \\ c_{t-2} \\ AX_{1t-2} \\ AX_{2t-2} \end{bmatrix} + \begin{bmatrix} e_t^{\tau} \\ \nu_{1t} \\ \nu_{2t} \\ \nu_{3t} \\ \vdots \\ 0 \end{bmatrix} \tag{9}$$

The measurement equation relates unobserved variables and observable variables

$$\begin{bmatrix} \Theta_t \\ AX_{1t} \\ AX_{2t} \end{bmatrix} = \begin{bmatrix} 1 & 1 & \cdots & \cdots & \cdots & \cdots & 0 \\ 0 & 0 & 1 & 0 & \cdots & \cdots & 0 \\ 0 & 0 & 0 & 1 & 0 & \cdots & 0 \end{bmatrix} \begin{bmatrix} \tau_t \\ c_t \\ AX_{1t} \\ AX_{2t} \\ c_{t-1} \\ AX_{1t-1} \\ AX_{2t-1} \end{bmatrix} \tag{10}$$

Following the conventional unobserved components notation, the correlation between innovations of the trend and the cycle is not explicitly modeled, see for example Harvey (1985), Clark (1987) or Mertens (2016). The vector of innovations to the trend and Z_t is assumed to be distributed as

$$\begin{bmatrix} e_t^{\tau} \\ \nu_t \end{bmatrix} \sim N(0, Q), \ \ with\ Q = \begin{bmatrix} \sigma_t^{\tau 2} & 0 \\ 0 & \Sigma_t \end{bmatrix} \tag{11}$$

2.2. Estimation

In this section, we summarize the estimation algorithm. We estimate the model via Markov-Chain Monte Carlo (MCMC) methods using a Metropolis-within-Gibbs algorithm and obtain smoothed estimates of the unobserved components.[8] The Gibbs sampler cycles through the following steps:

1. Set the starting values.
2. Conditional on a draw of the unobserved components A, Λ_t, and Q sample VAR coefficients from a normal posterior distribution.[9]
3. Conditional on the draw of the VAR coefficients in step 2 compute the VAR residuals v_{it}.
4. Draw the time-invariant α_{ij} elements of the variance-covariance matrix with a heteroskedastic linear regression as in Cogley and Sargent (2005).[10]
5. The volatilities of the reduced form shocks Λ_t are drawn using the date by date blocking scheme introduced in Jacquier et al. (2004).
6. The hyper parameters are drawn from their respective distributions.
7. Repeat steps 5–6 for the trend.

8. Conditional on the draws apply the Carter and Kohn (1994) algorithm to cast the unobserved components in a state space model as in Mumtaz (2010).
9. Go to step 1.

3. Estimation using simulated data

In order to assess the efficacy of the algorithm, we undertake a concise simulation exercise. The experiment involves the generation of two synthetic datasets, each comprising a target variable and three auxiliary variables.[11] The distinctive feature of the data-generating process (DGP) lies in the temporal variance of the reduced form errors characterizing both artificial series. Subsequently, the target variable, derived as the summation of a trend and a cycle, undergoes decomposition using three distinct filtering methods: the proposed filter, a homoskedastic variant thereof, and the HP-filter. The performance evaluation of each method is conducted through formal comparisons, gauged by the correlation between the true cycle and the estimated cycle (Kamber et al. (2018)). Furthermore, an in-depth exploration of the cyclical properties ensues, employing a turning point analysis that combines Dupraz et al. (2019)'s dating algorithm for turning point determination and the concordance index proposed by Harding and Pagan (2002).

As motivated in the introduction, the methodological framework advanced in this study is predicated upon the conceptual foundation that the financial cycle is approximated by a measure of the interrelation of aggregates reflective of macroeconomic imbalances. Consequently, our generated dataset emulates the two-sided relationship between the cyclical state variable and the auxiliary variables. Notwithstanding, establishing the suitable set of multivariate information poses a challenging econometric quandary in practical applications (see e.g. Kamber et al. (2018)). A plausible scenario arises wherein the econometrician lacks cognizance of the full set of auxiliary variables that are relevant to capture the financial cycle. This is especially relevant because the factors influencing the financial cycle can change over time, as explained in subsection 4.4. Therefore, we assess the efficacy of our suggested filter by deliberately excluding one of the auxiliary variables employed in the cyclical generation process from the estimation procedure. We refer to the case where not all auxiliary variables used in generating the artificial cycle are included as the "Incomplete Information" setting. Conversely, we term the case in which all the auxiliary variables are incorporated as the "Complete Information" setting.

In consideration of the extensive empirical evidence substantiating the prevalence of time variation in reduced form shocks within macro-financial time series across an extended temporal horizon (e.g. Cogley and Sargent (2005); Hubrich and Tetlow (2015)), adherence to our established baseline approach is warranted. Nonetheless, in order to systematically evaluate the efficacy of our proposed methodology under conditions of constant variance, we consider a supplementary artificial dataset, denoted as DGP 2. This deliberate departure from the prevailing time-varying framework aims to elucidate the robustness and performance characteristics of our approach in a homoskedastic environment.

The concordance index, as formulated by Harding and Pagan (2002), provides a systematic means to evaluate the alignment of turning points between the estimated cycles and the true cycle. This index quantifies the proportion of time during which the estimated reference cycles and the true-referenced cycle are in the same phase. A value of 1 indicates complete alignment, signifying that the two dating methods coincide in phase 100% of the time. In our initial assessment, we employ the dating algorithm proposed by Dupraz et al. (2019) to identify cyclical turning points. S_j signifies the classification of states produced by a particular method, where j corresponds to distinct filtering methods and set-ups. As explained in Camacho and Gadea (2022) this method builds on the change in the sign of the growth rate in the reference series. Taking S_{TRUE} as the states of the reference series, the concordance index can be expressed as:

$$IC_{j,TRUE} = T^{-1} \left\{ \sum_{t=1}^{T} S_{j,t}\ S_{TRUE,t} + (1 - S_{j,t}) \left(1 - S_{TRUE,t}\right) \right\} \tag{12}$$

The left-hand side of Table 1 presents the outcomes related to DGP 1, incorporating a dynamic error structure. As expected, the stochastic volatility (SVOL) specification with complete information demonstrates the highest correlation with the true cycle, aligning closely with the underlying data-generating process. Notably, employing a homoskedastic approach for cycle estimation results in a marginal reduction in correlation with the true cycle; however, the correlation remains substantially high. When the model is estimated with the exclusion of one auxiliary variable, labeled as "Incomplete," the correlation with the true cycle decreases to approximately 0.79 for the SVOL filter and more modestly to around 0.86 for the homoskedastic filter. The cycles estimated through complete model-based approaches (SVOL and Homoskedastic filters) exhibit a high concordance with the true cycle. A decline is more substantial for the SVOL filter under incomplete information than for the Homoskedastic filter.

Table 1. Monte Carlo simulations

		DGP 1		DGP 2	
		Correlation	Concordance	Correlation	Concordance
SVOL	Complete	0.969	*0.955*	0.977	*0.910*
	Incomplete	0.785	*0.820*	0.840	*0.860*
Homoskedastic	Complete	0.917	*0.792*	0.976	*0.944*
	Incomplete	0.863	*0.781*	0.876	*0.848*
HP-filter	One-sided	0.759	*0.747*	0.727	*0.780*

Results based on the cyclical component of the target variable $\Theta_t = \tau_t + c_t$. For both DGPs $T = 220$. *Correlation* refers to correlation between the true cycle and the estimated cycle. *Concordance* is the concordance index as proposed by Harding and Pagan (2002). DGP 1 assumes a time-varying variance process. The cycle and two auxiliary variables are generated as $Z_t = X_t B + A^{-1}\Lambda_t^{0.5}\epsilon_t, \quad \epsilon_t \sim N(0, I_4)$, the trend follows $\tau_t = \tau_{t-1} + \upsilon_t\sqrt{exp(ln\lambda_t^{\tau})}, \quad \upsilon_t \sim N(0, 1)$. DGP 2 imposes a constant variance process with $Z_t = X_t B + \Omega^{0.5}\epsilon_t, \quad \epsilon_t \sim N(0, I_4)$ for the cycle and $\tau_t = \tau_{t-1} + \upsilon_t \sim N(0, 1)$ for the trend.

The right-hand side of Table 1 displays the results based on DGP 2, the constant variance data-generating process. For its proximity to the underlying data-generating process, the homoskedastic filter unsurprisingly displays the best performance. However, that of the SVOL is comparable, both in terms of the correlation with the true cycle and the concordance index. This indicates that even when the underlying data-generating process is characterized by a time-invariant error structure, the SVOL filter is a suitable method to extract cycles from those time series. In this setting, the difference in the correlation with the true cycle in the "Incomplete information" setting is smaller than when the underlying series builds on a heteroskedastic error structure. In both cases, the HP-filter displayed the weakest performance across specifications.

4. Empirical application

This section presents the results of the country-level estimates for the financial cycle for the USA and the UK based on our preferred specification. Model selection is performed based on the models' log-scores (LS). For both countries we assume the financial cycle reflects appropriately the buildup of vulnerabilities and the subsequent materialization of risk which occurred with the onset of crisis episodes documented by Drehmann and Juselius (2014), and is characterized by a strong persistence. The appropriateness of the proposed specification with regards to alternative data transformations and modeling choices is evaluated in terms of its capacity to fit the target variable and its early warning properties to signal the emergence of banking crises. Then, we discuss the role of stochastic volatility in the estimation of the financial cycle. In this context, we examine the particle weighted Kalman gains of the financial cycle, which is a measure of its sensitivity to unexpected changes in the observable variables across time. Finally, to get an insight of the main factors driving the financial cycle, the following functions of the VAR coefficients are discussed: forecast error variance decomposition and historical decomposition.

4.1. Data

We apply the multivariate filter as described in section 2.1 to the credit ratio.[12] We include this variable in levels in order to retain the information contained in the trend. The auxiliary variables reflect deviations from equilibrium developments and contribute to estimate the cyclical component. We use quarterly data for the USA ranging from 1961:Q1 to 2019:Q1 and for the UK ranging from 1963:Q2 to 2019:Q1. The data sources and transformations are listed in Table 2.

Table 2. Variables and sources

			Transformations	
Variable	Series	Source	Baseline	Alternative
United States 1961:Q1-2019:Q1				
Target	Credit ratio	BIS	Total credit to the private non-financial sector as % of GDP.	
Auxiliary I Household vulnerabilities	House-price-to-income ratio	OECD; FRED; Shiller Home Price Index	Ratio of residential house prices and disposable income, deviations from 10-year averages, rolling basis.	Level: Log level of residential house prices. Growth: Log differences of residential house prices.
Auxiliary II Financial conditions	Excess Bond premium	FRB; FRED	Moody's seasoned BAA corporate relative to Federal Funds Rate, 1961:Q1–1972:Q4; Excess bond premium, 1973:Q1–2019:Q1.	
Auxiliary III Economic performance	Unemployment rate	FRED	Deviations from 10-year averages, rolling basis.	
United Kingdom 1963:Q2-2019:Q1				
Target	Credit ratio	BIS	Total credit to the private non-financial sector as % of GDP.	
Auxiliary I Household vulnerabilities	House-price-to-income ratio	OECD; ONS	Ratio of residential house prices and disposable income, deviations from 10-year averages, rolling basis.	Level: Log level of residential house prices. Growth: Log differences of residential house prices.
Auxiliary II Financial conditions	Corporate bond spread	BoE; Global Financial Data	Spread Corporate bond yield for the UK relative to 10-year government bond yield	
Auxiliary III Economic performance	Unemployment rate	BoE; ONS	Deviations from 10-year averages, rolling basis.	

Bank of England (BoE); Bank of International Settlements (BIS); Federal Reserve Economic Data (FRED), Federal Reserve Board (FRB); Organisation for Economic Cooperation and Development (OECD); Office for National Statistics (ONS). Deviations from 10-year averages defined as quarterly averages including observations from period $(t-40)$ till t.

Moreover, buildup phases of the financial cycle were found to have a good properties to signal banking system distress (e.g. Drehmann et al. (2012); Borio and Lowe (2004)).

Hence, the evaluation of credit developments seems fundamental to capture the financial cycle. Nonetheless, uniquely considering its univariate dynamics might be insufficient for a number of reasons. First not every credit boom precedes a financial crisis (Mendoza and Terrones (2008);

Gorton and Ordonez (2014)). Second, given the complexity of the inter-linkages between the financial system and the real economy, a single indicator does not allow to pin down various dimensions related to the buildup of macro-financial vulnerabilities.

The relationship between the financial system and the real economy is continuously evolving. For instance, while in the late 1990s risk appetite was elevated in equity and business credit markets, in 2004 risk taking had shifted towards other sectors such as the housing market. Based on this idea, our method allows for a flexible inclusion of variables to measure the evolution of cyclical imbalances. In the following, we will analyze the coincidence between credit, financial conditions, asset prices and economic activity.

As boom-bust cycles in real estate prices are considered fundamental sources of financial fragility, we will assess valuation pressures in the mortgage market through the house-price-to-income ratio (hp-to-income) relative to a 10-year moving average. Deviations from the long-term trend represent a measure of housing market valuations related imbalances and subtracting the long-run average we minimize the influence of structural drivers (see Cecchetti (2008); Reinhart and Rogoff (2010) or Anundsen et al. (2016)). Moreover, as real estate prices share relevant cyclical similarities with credit, its inclusion will help to reduce distortions in the cycle identification by minimizing missing parts of the captured cyclical dynamics (see Claessens et al. (2012); Schüler et al. (2020); Galati et al. (2016); Rünstler and Vlekke (2018)).

Financial conditions refer to the state and functioning of financial markets that affect economic behavior. We include this risk channel through a measure that reflects financial sector risk (e.g. Guichard et al. (2009), Hatzius et al. (2010) or Nicoletti et al. (2014)). While for both countries the same auxiliary variable is included, due to data availability, the measures of aggregate risk differ: for the USA we include the Excess Bond Premium (EBP) as in Gilchrist and Zakrajšek (2012) and for the UK we consider corporate spreads. The EBP is a component of corporate bond credit spreads that is not directly attributable to expected default risk and provides an effective measure of investor sentiment or risk appetite in the corporate bond market. Arregui et al. (2018) finds that corporate spreads are amongst the financial variables that contribute most to countries' financial conditions.

Periods of low risk can be conducive of a greater buildup of systemic risk through higher levels of leverage, the so-called volatility paradox (Brunnermeier and Sannikov (2014)). In line with this literature, low values of the auxiliary variable that reflects financial sector risk should contribute positively to upward tendencies in the financial cycle. We therefore include the second variable with a negative sign in both countries' model. Through this transformation a spike in this series will be reflective of a materialization of risk and push the financial cycle downwards.

Rapid decreases in unemployment are often interpreted as a sign of economic overheating. In order to capture the buildup of potential vulnerabilities in the real economy we incorporate the deviations from long-run average levels in unemployment as a third auxiliary variable. Decreases in unemployment should contribute positively to the financial cycle, therefore, this variable will enter the model with a negative sign.

4.2. Model selection

Following Geweke and Amisano (2010) we compare different levels of prior tightness based on the predictive density of the target variable Θ_t. Scoring rules evaluate the accuracy of the predictive densities by assigning a numerical score based on the forecast and the subsequent realization of the variable (Mitchell and Wallis (2011)). For each level of prior tightness κ we compute:

$$log\ p(\Theta_{iT}|\Theta_{iS}, \kappa) = \sum_{t=S+1}^{T} log\ p(\Theta_{it+h}|\Theta_{it}) \tag{13}$$

where κ takes values between 0.2 and 0.9,[13] $\log p(\Theta_{it+h}|\Theta_{it})$ denotes the log score for the predictive density of the target variable, h is the horizon of the forecast and $t = S+1, \ldots T$ is the evaluation period for $S < T$. The evaluation period is the last 10 years of the sample (2009:Q1 to 2019:Q1). Table 3 shows the 1 year ahead log-scores, that is, $h = 4$, for each country model. On this basis we select the following values: $\kappa = 0.9$ for the USA and $\kappa = 0.8$ for the UK. As in Bańbura et al. (2010), the sum of coefficients prior is set as $\lambda = 10\tau$. This reflects loose prior beliefs and is proportional to the overall tightness parameter κ, selected based on the score in Table 3 that maximizes the forecasting accuracy of the model.

Table 3. Four periods ahead predictive log-scores (LS) averaged

	Prior tightness (κ)							
	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US	−17.398	−8.094	−5.4537	−5.1169	−4.896	−4.770	−4.5388	−4.344
UK	−25.816	−23.668	−19.567	−18.353	−14.749	−12.749	−9.448	−9.942

Ordered by descending levels of prior tightness for the target measure.

4.3. Financial cycle estimates

4.3.1. Baseline specification

In this subsection we report the country-level estimates of the financial cycle, as generated from the HP-filter, our baseline specification presented in section 2.1 and a time-invariant version of the latter (Section C of the Appendix provides details on the specification). These three country-by-country estimates for the financial cycle are displayed in Figure 1 providing a comparison

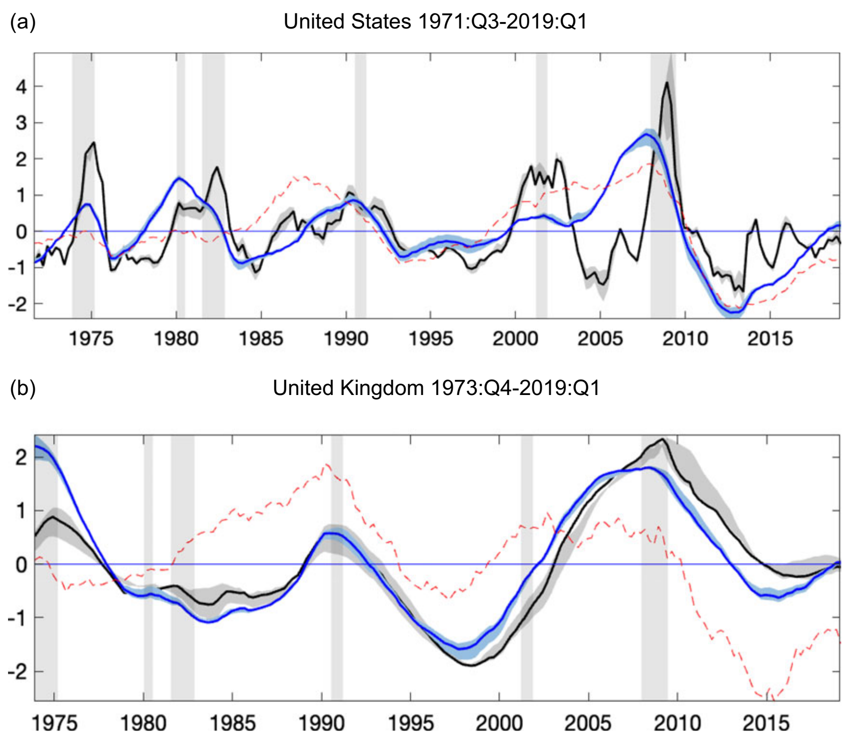

Figure 1. Comparison across financial cycle estimates.
Note: Stochastic volatility (blue), homoskedastic (grey) and Basel-gap (red). Solid line shows the median of the posterior distribution, the shaded area represents the 68% error band. The dashed lines represent the Basel-gap. Grey vertical areas display the NBER economic recessions.

along two dimensions: on the one hand, it shows how multivariate model-based filters perform in comparison to non-parametric filters, and second, it illustrates the difference between a filter with a time-varying error structure and one with constant variance. The estimated trends are displayed in Section E of the Appendix. Estimating the cycle with a homoskedastic error structure allows to shed some light on the potential gains derived from the inclusion of a time-varying error structure. The role of this modeling choice in the estimation will be further explored in subsection 4.3.2.

The fluctuations of the financial cycle can be broadly divided into two stages: upward tendencies can be interpreted as buildup in the level of macro-financial imbalances, while downward trajectories can be read as periods of risk materialization or dissipation. Based on Drehmann and Juselius (2014) the sample covers two banking crises: the first in the early 90s known as the "Savings and Loans Crisis" (SLC) and the second being the "Global Financial Crisis" (GFC) in 2007. In the following paragraphs we discuss via visual comparison the early warning properties of the financial cycle estimated with the stochastic volatility filter (blue) with those of the Basel-gap (dashed red line). Subsection 4.3.4 provides supporting evidence from an analytical approach.

Similar to the Basel-gap, our estimate for the USA displays a sustained upward trajectory in the quarters prior to the SLC and to the GFC. A striking difference between the two approaches is that the estimated US financial cycle peaks already four quarters ahead of the GFC, while the Basel-gap reaches its maximum value one quarter past the crisis outbreak, that is, 2007:Q4. This property is indicative of a superior early warning capacity of the financial cycle with respect to the Basel-gap. In the periods following the GFC the decay of the financial cycle is as rapid as the Basel-gap's and both measures capture the turn in the cycle in 2013. Nevertheless, due to the inherent high persistence of the HP filer, the Basel-gap remains below the zero line and therefore does not reflect the expansion period that follows the post-GFC recovery in late 2016. The estimate of the UK financial cycle and the UK Basel-gap display an increase in the level of cyclical vulnerabilities prior to both crisis episodes captured in our sample. As it is the case for the USA, the financial cycle peaks ahead of the Basel-gap prior to the GFC. Also, in the UK the financial cycle displays a less persistent downturn during the recovery period than the HP-filter estimate.

Building on the application of the proposed method to two economies, we find that our estimate of the financial cycle signals the increase in systemic risk prior to past banking crises earlier than the Basel-gap. Moreover, the financial cycle captures the turn in the cycle in post-crisis periods at a more realistic rate than the Basel-gap. The latter estimate is determined by the statistical properties of the HP-filter, whereby large cyclical fluctuations have a persistent impact on the estimated trend, leading to persistently negative values after large drops. On the contrary, the flexibility of our approach is able to capture cyclical turns in a more timely fashion.

4.3.2. The role of stochastic volatility

A comparison across the financial cycle estimates from both multivariate approaches displayed in Figure 1 indicates that the relevance of including stochastic volatility in our estimates varies across countries. For the USA there are notable differences across specifications, whereas for the UK the estimated cycles are broadly similar.

Moreover, for the USA we observe a larger variability in the model-based homoskedastic estimates (grey) than in the time-varying estimates (blue). This could be an artifact of the inability of the homoskedastic filter to account for financial and macroeconomic volatility. Hence, in the constant variance-covariance setting, the cycle could be capturing movements in the volatility that are not modeled, thereby exaggerating the variability of cyclical fluctuations. This argument is articulated in Cogley and Sargent (2005) through the comparison of a time-varying parameter model with constant error structure and a constant parameter model with a time-varying error structure. Moreover, as noted earlier, time variation has been found to be statistically important to the modeling of macroeconomic and financial interrelations (e.g. Hubrich and Tetlow (2015)).

A byproduct of the multivariate stochastic volatility specification, are the estimates for the uncertainty of the latent and observable variables. Their inspection provides an additional angle to understand the heterogeneity in the country results, since the change in the volatility of the trend and cycle in the UK appears to be smaller than in the USA. The initial pair of subfigures within Figure E.4, situated in Section E of the Appendix, present the stochastic volatilities characterizing both the trend and cycle components for the USA and the UK. In both countries the volatility became more pronounced after 2000. Also, the estimated trend moved more rapidly in recent times as illustrated in Figure E.2 within Section E of the Appendix. On the other hand, the cyclical movements were more pronounced before the 1980s for both countries. These findings supports the literature that associates the Great Moderation period, starting from the mid-1980s, with a lower volatility (see McConnell and Perez-Quiros (2000), Cogley and Sargent (2005) or Primiceri (2005)).

The larger volatility of the trend and cycle components in the USA partially explains the varying role of heteroskedasticity across countries. However, the question persists regarding whether the clarity in depicting the buildup of macro-financial vulnerabilities in the financial cycle estimates presented in Figure 1 can be attributed to the inclusion of multivariate information or the presence of stochastic volatility. We endeavor to isolate the impact of individual features by generating financial cycle estimates within various frameworks. Our exploration encompasses both univariate specifications of the filter and multivariate approaches. In both, stochastic volatility is included for either the trend component alone, the cyclical component alone, both components simultaneously, or a fully homoskedastic approach is adopted.

Two conclusions emerge from the exploration, the results are displayed and analyzed in detail in Section E of the Appendix: (i) Multivariate information is essential to synthesize macro-financial imbalances and cyclical systemic risk dynamics; (ii) The incorporation of stochastic volatility in the cycle proves to be more consequential than its inclusion in the trend. Additionally, restricting stochastic volatility exclusively to the trend, while employing a homoskedastic error structure for the cycle, yields less informative results compared to the fully homoskedastic case.

Another major advantage of our heteroskedastic approach is allowing for time variation in the Kalman gains. This implies that the sensitivity of the unobserved components to signals from the observable variables can evolve dynamically. In order to extract the Kalman gain estimates, we re-estimate the multivariate stochastic volatility state space model presented in Section 2 with a Rao-Blackwellized particle filter following Mertens (2016). We provide details of the particle filter in Section F of the Appendix.

The Kalman gain quantifies the marginal impact of an individual variable within a cross-section of signals. Although it lacks a structural interpretation, the weighted average of Kalman gains highlights the sensitivity of cycle estimates to various input variables, allowing an exploration of which signals from the auxiliary variables receive significant weighting from the filter over time.

Figure 2 displays the Kalman gains for the financial cycle. Overall, while real estate valuations were important throughout the sample for both countries, the sensitivity of the cycle to changes in financial conditions was more volatile: In the USA the estimated cycle was largely influenced by the EBP until the end of the Volcker disinflation, while in the UK the cycle was taking the strongest signal from corporate spreads in the periods surrounding the "Dotcom" crisis. This property further supports our choice of the heteroskedastic filter to extract financial cycles.

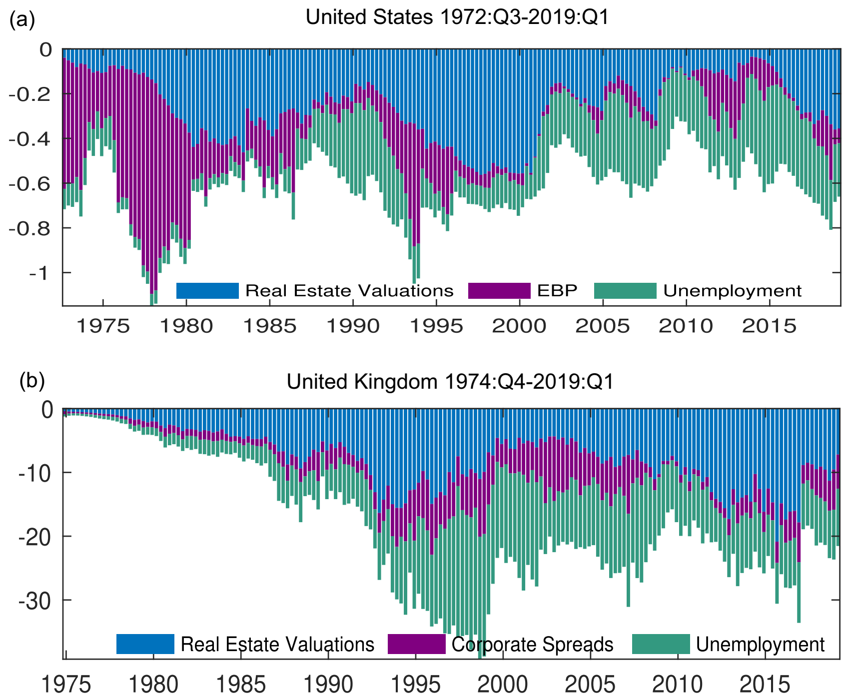

Figure 2. Kalman gains for the financial cycle.
Note: Particle-weighted Kalman gains computed from the particle filter. Estimation based on whole sample length but first year of observations is removed for better visualisation.

4.3.3. Alternative specifications

In this subsection we compare the financial cycle estimates of the Baseline specification and two alternative data transformation choices against the Basel-gap by means of their marginal likelihood. In the subsequent section we will also explore the comparative performance of these models in terms of their early warning properties.

As described in Section 4.1 the baseline specification considers the house-price-to-income ratio and unemployment rate with respect to its 10-year moving average as first and third auxiliary variables respectively. This transformation allows to reduce the influence of structural drivers and reflects our aim to inform the estimation of the financial cycle via cyclical fluctuations in vulnerabilities.

To assess the performance of the baseline specification, we borrow from existing approaches that estimate the financial cycle via multivariate filters to establish two alternative specifications. In line with Rünstler and Vlekke (2018), that include the log level of the index of real residential property prices, the specification (which we label "Level"), takes the log-level of the house-price-to-income ratio as first auxiliary variable. The second alternative specification borrows from Berger et al. (2022), who include real residential property prices for USA in log differences and do not apply any transformation to the excess bond premium and the civilian unemployment rate. This specification (which we label "Growth") takes the first difference of the house-price-to-income ratio as first auxiliary variable. Consistently with the aforementioned literature, no transformation is applied to the second and third auxiliary variables. Table 2 offers an overview and details of various specifications.

Grant and Chan (2017) develop a Bayesian generalization of the HP-filter.[14] Using this model-based approach and calibrating it to the Basel-gap such that λ is fixed ($\lambda = 400000$) allows us to formally assess the model fit and compare the HP-filter estimates with other models. We adjust the model-based approach of Grant and Chan (2017) to obtain one-sided estimates of the HP-filter, this is running the standard two-sided HP-filter successively with each new observation (see Mehra (2004) or Ganev (2020)). Then the marginal likelihoods are computed using the adaptive importance sampling method proposed in Chan and Eisenstat (2015).

We compare the three models (i) SVOL multivariate filter, (ii) Homoskedastic multivariate filter and (iii) HP-filter in a formal Bayesian model comparison via the marginal likelihood. The marginal likelihood of the multivariate filters is computed using the methods described in Geweke and Amisano (2010).[15] Table 4 reports each model's marginal likelihood. The model's probability density is evaluated for the target variable, that is, the credit ratio.

Table 4. Marginal likelihoods of alternative filtering methods

Specification	Method	US	UK
Basel-gap	One-sided HP-filter	−567.159	−600.551
Baseline	**SVOL**	−443.798	−451.859
	Homoskedastic	−563.408	−488.412
Level	SVOL	−515.211	−461.077
Growth	SVOL	−554.358	−592.489

Log marginal likelihoods of competing models to extract the financial cycle. The model's probability density is evaluated for the target variable.

According to the marginal likelihood the HP-filter has the weakest performance in both countries. This supports the findings in Morley and Piger (2012) and Chan and Eisenstat (2018) who compare the performance of a range of models to estimate the output gap and find that the HP-filter is the model that most contradicts the data. Overall, the data favor the Baseline (SVOL) specification over the other alternatives. The marginal likelihood is substantially larger for the Baseline (SVOL) model with respect to the one-sided HP-filter, however the difference to the other two multivariate and heteroskedastic specifications is not as large. Moreover, the marginal likelihood indicates that the Level specification is preferred by the data over the Growth specification. In the next subsection we show that this preference also holds concerning the early warning properties of the models.

In a homoskedastic setting the marginal likelihood of the baseline specification is around 0.30 times lower for the USA while only about 0.10 times smaller in the UK. The fact the inclusion of a time-varying error structure in the UK does not alter much the results is, as argued in subsection 4.3.2, probably related to the small variability of the estimated volatility of the trend and cycle across time (Figure E.4 in Appendix). However, for the USA, allowing for a heteroskedastic error structure seems key, since in the homoskedastic setting the model fit of the multivariate baseline specification is not very different from that of the Basel-gap.

4.3.4. Early warning properties

In this subsection we evaluate and compare the ability to signal the emergence of systemic crises of our proposed indicator to that of the Basel-gap. We follow Drehmann and Juselius (2014) and Anundsen et al. (2016) who apply the receiver operating characteristics curve to map the two types of signaling errors that can be made in a binary setting: (i) failure in predicting a crisis (Type I error) and (ii) issuance of false positive signals (Type II error). Specifically, the area under the Receiver Operating Curve (AUROC) is an easy interpretable summary measure of the signaling performance as it increases with the predictive power of the indicator. Hence, a perfect indicator has an AUROC of 1, while an uninformative indicator has an AUROC of 0.5.

Macroprudential policymakers require an indication of emerging vulnerabilities ahead of a crisis such that preemptive policy measures can be taken sufficiently in advance to be effective. This is of particular relevance to the setting of the Countercyclical Capital Buffer (CCyB) because of the 12-month implementation lag (EU (2013)). However, policy action should also not occur too early given the costs associated with the implementation macroprudential policies (e.g. Richter et al. (2019)). In line with Anundsen et al. (2016), our evaluation targets the likelihood that the economy is in a period of rising systemic vulnerabilities 12 months ahead of the outbreak of a banking crisis. Moreover, as in Bussiere and Fratzscher (2006) the observations in the six quarters succeeding a crisis are omitted to avoid post-crisis bias.

On this basis we construct our binary dependent variable $D_{i,t}$ that takes the value one during the 5- to 12-quarter period ahead of the two banking crises considered in our sample, that is, the SLC and the GFC, and, additionally, for the UK in the period between 2017:Q3 and 2019:Q1. The reason for this classification being that the Bank of England (BoE) announced in 2017:Q3 a non-zero CCyB rate.[16] Against this background, we believe that interpreting those quarters as periods of risk dissipation would be misleading. We estimate a standard logit model for each analyzed method separately using maximum likelihood techniques and correcting for potential clustering along the country dimension (Janes et al. (2009)).

Table 5 summarizes the main results, it displays the estimated AUROC and its significance level corresponding to the different multivariate specifications and the Basel-gap. The message from Table 5 is that the SVOL model with the baseline specification is the best performing early warning indicator of systemic crises and reports the highest Pseudo R^2. The Basel-gap has a slightly worse performance but still provides a high information content, which is unsurprising as the good early warning properties of the Basel-gap are well established (e.g. Drehmann et al. (2012)). Turning to the Level specification estimated with the SVOL filter, it ranks lower in terms of its performance in signaling banking crises than in terms of its comparatively good model fit (see Table 4).

Table 5. Assessing the ability to signal systemic crises: comparative analysis of alternative methods via the area under the receiver operating curve (AUROC)

Specification	Method	AUROC	Pseudo R^2
Basel-gap	One-sided HP-filter	0.799**	0.162
Baseline	**SVOL**	**0.835****	0.287
	Homoskedastic	0.658**	0.037
Level	SVOL	0.752**	0.133
Growth	SVOL	0.558	0.003

The asterisks denote significance levels: *10%; **5%.

Combining the results in Tables 4–5 and stressing the fact that the only difference between the Baseline and level specification is the transformation of the real estate valuation variable, the following conclusions can be drawn: The evolution of house prices is relevant to achieve a model fit that is superior to the Basel-gap. However, to beat the Basel-gap in predicting future financial crisis a measure that additionally tracks the evolution of borrower vulnerabilities is needed. This supports the finding in Anundsen et al. (2016) that excessiveness in house prices is a relevant determinant of financial crises. Moreover, the results for the Growth specification are not statistically different from an uninformative indicator, suggesting that very short term dynamics in the real estate market are not informative to signal financial crisis. This might be a result of its inability to capture the buildup of emerging vulnerabilities.

The Homoskedastic specification in the third row of Table 5 corresponds to the model-based estimates (grey) in Figure 1. As discussed in subsections 4.3.1 and 4.3.2 the results for the USA displayed large variability along with poor early warning properties. For the UK the difference across specification of the covariance structure was small. Nonetheless, in the UK the homoskedastic estimates peaked at a later stage than those for the SVOL model ahead of the GFC and didn't decay sufficiently to enter a risk dissipation phase in the crisis aftermath. Finally, the low AUROC value (0.658) further supports the intuition, gained by visual inspection, of the homoskedastic model not being as well suited as the SVOL model to signal the emergence of banking crises.

4.4. The role of macro-financial factors in driving the financial cycle

In the following two subsections we discuss the results from the forecast error variance decomposition (FEVD) and the historical decomposition (HD) as a means of summarizing the underlying factors driving the financial cycle.

It should be noted that the Cholesky-type decomposition that allows to estimate Σ_t as in equation (8) is used as a method to estimate the variance and not as an identification strategy for the structural shocks. Therefore, the order of the variables is arbitrary. The results that build on the estimated parameters such as those presented in this section are reduced form estimates and only indicative of underlying structural relationships.

4.4.1. Forecast error variance decomposition

The FEVD measures the contribution of a specific shock to the variability of the forecast error for the observable and unobservable variables in our model. In other words, it describes in absolute terms which shock is more important in driving the realization away from the forecast and is computed at every point in time using the estimated (non-dynamic) parameters and the volatilities.[17]

At the medium-term horizon the housing market valuations shock is the variable that contributes the most to the forecast error variance decomposition of the financial cycle of the USA and also of the UK. During the pre-crisis periods explaining around 60% in the late 80s and up to 90% in the USA and 80% before and after the GFC. For both countries the risk appetite shock explains a greater share of the forecast error variance in years of financial turbulences. For the USA during the SLC this accounted for around 10% of the Forecast error variance, in the years around the "Dotcom" crisis of the 2000s up to 20%in and 30% between 2007 and 2008. With respect to the broader cyclical dynamics in the USA the contribution of unemployment amounted to about 35% in the years surrounding the economic recession that started at 1973.

4.4.2. Historical decomposition

The HD measures the contribution of each shock to the deviations of the realized observations from its baseline forecasted path. It decomposes the observed data into a deterministic component and the cumulated effects of structural shocks. Through the historical decomposition we estimate the individual contributions of each structural shock to the movements in the financial cycle.

Figure 3a shows the results for the de-trended median posterior estimate for the US financial cycle, represented by the red line. The results suggest heterogeneity in the patterns that preceded the two banking crises that are covered in the sample. The years prior to the banking crisis of 1988 were characterized by positive contributions of the risk appetite shock.[18] Hence decreases in the EBP contributed positively to the buildup in the level of macro-financial imbalances. This result supports research that stresses the potential of low volatility fostering leverage and through that channel spurring risk taking, with the potential for a destabilizing unfolding following spikes in volatilities (Brunnermeier and Sannikov (2014)).

During the years ahead of the systemic crisis of 2007 positive shocks to housing market valuations and decreases in unemployment contributed to the upward movement in the financial

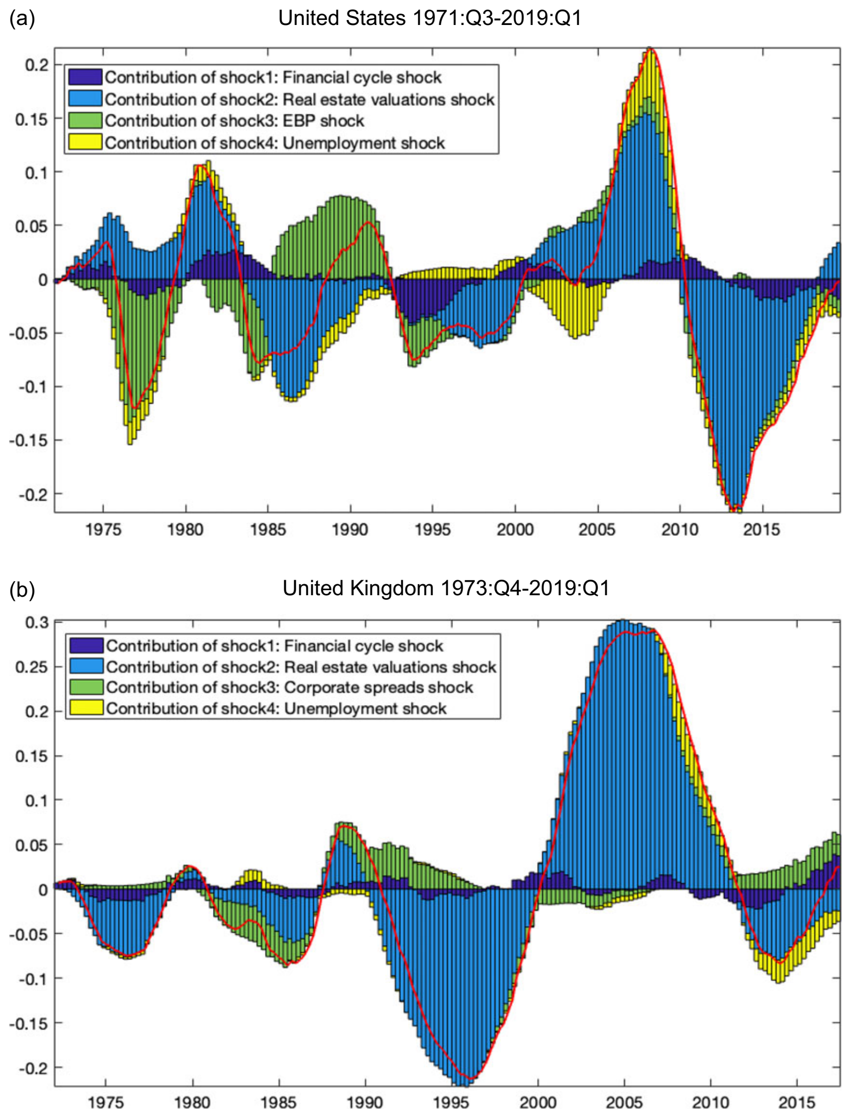

Figure 3. Historical decomposition of the financial cycle.
Note: Solid line represents the de-trended median posterior estimate.

cycle. The decompositions also demonstrate that the increase in the cycle after 2014 can be largely attributed to positive real estate valuations shocks as well as to an improvement of the credit market sentiment. Overall the influence of housing market valuations shocks on the financial cycle increased over time as these shocks have played a much smaller role in times prior to 2005 than afterwards.

The historical decomposition of the UK financial cycle in Figure 3b displays how between 1990 and 2010 shocks to real estate valuations were the main sources of deviations of the financial cycle from its baseline path in the UK. Between 2012 and the first quarter of 2019 shocks to financial conditions represented by the corporate credit spread were an important driver of the financial cycle away from its expected path. A possible explanation could be the corporate spread compression observed during the period.[19]

5. Conclusion

The GFC raised new challenges for policymakers, in particular in relation to the limitations of traditional macroeconomic policies to contain macro-financial imbalances. This has lead to the development of analytical tools that capture the evolution of financial misalignments, the most prominent being the Basel-gap. Nevertheless, some of the characteristics underlying the Basel-gap such as an univariate set-up or a highly persistent trend reduces its precision in measuring the buildup of cyclical risk. This paper addressees these shortcomings by developing an unobserved components model with stochastic volatility to decompose the credit ratio into trend and cycle components.

We apply our model to analyze the financial cycles in the USA and the UK. By explicitly modeling the joint dynamics of observed and latent variables in the state space, we move beyond the univariate properties of credit. Our results show that our approach provides more informative estimates of the financial cycle compared to frequency-based indicators commonly utilized by policymakers. Specifically, our model not only demonstrates superior early warning capabilities for banking crises but also excels in terms of data fit for decomposition exercises, as evidenced by a higher marginal likelihood. Remarkably, our method maintains its effectiveness even when the underlying series exhibit a time-invariant error structure.

We document three key characteristics of the financial cycle based on distinctive patterns observed in past crises. Firstly, there was an increased sensitivity of the financial cycle to changes in real estate valuations during the post-90s period. Secondly, the sensitivity of the cycle to changes in financial conditions displayed volatility and country-specific patterns. In the USA, their influence on the estimated cycle remained substantial until the conclusion of the Volcker disinflation. In the UK, the cycle was most responsive to corporate spreads during periods surrounding the 'Dotcom' crisis. Finally, our reduced form estimates suggested that the banking crisis of 1988 was preceded by positive contributions from the risk appetite shock, while the primary source of vulnerabilities emanated from the housing market in the run-up to the GFC. Moreover, aligning with the Great Moderation literature, the estimated volatility of the cyclical component in the credit ratio for the USA and the UK decreased in the 1980s.

Furthermore, based on data up to 2019:Q1, we find a positive financial cycle for the USA. Similar to the period preceding the GFC, we identify emerging risks associated with housing market valuation issues. In the case of the UK, our analysis indicates an upward trajectory of the financial cycle at a pace exceeding that suggested by the Basel-gap. While our results point in this direction, a more in-depth analysis of the distributional aspects, both geographically and by income level, would contribute to refining this assessment.

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Supplementary material. To view supplementary material for this article, please visit https://doi.org/10.1017/S1365100524000154

Notes

1 The Basel III legislation recommends to measure the financial cycle through the HP-filter in order to inform the countercyclical capital buffer (CCyB) calibration (see Bank for International Settlements (2010)). This specific measure is also known as the Basel-gap.

2 In the following we will refer to the credit-to-GDP ratio as the credit ratio and to the credit-to-GDP gap as the credit gap or financial cycle.

3 Our algorithm builds on Mumtaz (2010) extension of a time-varying parameter vector autoregressive (VAR) model of dynamic volatility by an enlarged version of the factor augmented VAR by Bernanke et al. (2005).
4 Hubrich and Tetlow (2015) analyze whether the shifts in VAR coefficients and stochastic shocks coincide with those of established events in US economics and financial history and finds that the linkages between financial stress and the macroeconomy display non-linear dynamics.
5 Lang and Welz (2018) and Galán and Mencia (2018) apply multivariate unobserved components models of trend-cycle decomposition to estimate the financial cycle and Schüler et al. (2020) introduce spectral analysis to isolate country-specific financial cycle frequencies.
6 In the unobserved components representation it is explicitly accounted for the fact that more than one ARIMA model will be able to provide a representation that is consistent with the properties of the correlogram observed in the data, for more information consult Harvey (1985) or Clark (1987).
7 Also see Carriero et al. (2016).
8 Note that we obtain smoothed estimates via MCMC methods and filtered estimates with the particle filter. Sections A and B of the Appendix contain further details on the prior distributions and sampling method.
9 We start the algorithm with a bandpass-cycle extraction calibrated to approximate the financial cycle as in Claessens et al. (2012). The vector of coefficients is drawn from a posterior distribution with mean and variance as in Clark (2011).
10 As in Cogley and Sargent (2005) our model is based on the simplifying assumption that the innovation to the i-th variable has a time-invariant effect on the j-th variable. Through this transformations the VAR residuals are contemporaneously uncorrelated and therefore the stochastic volatilities can be drawn independently.
11 For more details on the data-generating process, refer to Section D of the Appendix.
12 Consistent with the terminology and notation introduced in section 2.1 the credit ratio will be the target variable $\Theta_t = CreditRatio_t$.
13 Based on the values commonly used in the literature (Canova (2011)) we report the results for the a prior value starting at 0.2. The historical decomposition and the forecast error variance decomposition show that very tight priors, that is, $\kappa = 0.1$ disregard the information contained in the auxiliary variables while putting most of the weight on the own lags of the cycle. Hence, in order to capture the joint variance of all the variables that conform the model very tight priors should be avoided.
14 This approach builds on previous papers on the Bayesian interpretation of the HP-filter as a posterior mean given a certain prior for τ. For instance, Kitagawa and Gersch (1984) and Gersch (1993) derive an explicit expression for a smoothing prior for τ that is equivalent to the HP trend.
15 Geweke and Amisano (2010) compute the marginal likelihood through the models predictive density.
16 Refer to Bank of England's Financial Policy Committee statements 2017:III-2019:I for a review of the policy decisions.
17 A visual representation of the FEVD is available Section E of the Appendix.
18 The reader should bear in mind that this variable enters the model with a negative sign.
19 For its to potential to foster an abrupt and disorderly reversal of financial market sentiment, the compressed corporate risk premia is regraded as a driver of cyclical systemic risk. See for example the Bank of England's Financial Policy Committee statements of 2016:II or 2018:I.

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