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Abstract

This paper develops a multivariate filter based on an unobserved component trend-cycle model. It incorporates stochastic volatility and relies on specific formulations for the cycle component. We test the performance of this algorithm within a Monte-Carlo experiment and apply this decomposition tool to study the evolution of the financial cycle (estimated as the cycle of the credit-to-GDP ratio) for the United States, the United Kingdom and Ireland. We compare our credit cycle measure to the Basel III credit-to-GDP gap, prominent for its role informing the setting of countercyclical capital buffers. The Basel-gap employs the Hodrick-Prescott filter for trend extraction. Filtering methods reliant on similar-duration assumptions suffer from endpoint-bias or spurious cycles. These shortcomings might bias the shape of the credit cycle and thereby limit the precision of the policy assessment reliant on its evolution to target financial distress. Allowing for a flexible law of motion of the variance covariance matrix and informing the estimation of the cycle via economic fundamentals we are able to improve the statistical properties and to find a more economically meaningful measure of the build-up of cyclical systemic risks. Additionally, we find a large heterogeneity in the drivers of the credit cycles across time and countries. This result stresses the relevance in macro prudential policy of considering flexible approaches that can be tailored to country characteristics in contrast to standardized indicators.

JEL classification: C32, E32, E58 ,G01, G28

Keywords: Credit imbalances, cyclical systemic risk, financial cycle, macro-prudential analysis, multivariate unobserved-components models, stochastic volatility

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1 Introduction

Periods of excessive credit growth, fast output growth and rising asset prices have often preceeded financial crashes (e.g. Kindleberger(1978)[60] and Reinhart and Rogoff(2009)[68]). A common factor in crisis build-up periods is excessive risk taking fuelling unsustainable credit booms, characterized by resource misallocation and low productivity. However, every crisis develops in a different manner as the types of distortion vary from crisis to crisis. For this reason, it is important to avail of monitoring tools which allow not only to size aggregate risk, but also to decompose it into the underlying factors associated with systemic imbalances. In this paper, we apply an unobserved components model with stochastic volatility to credit to GDP ratio in the US, the UK and Ireland identifying the cycle component through the associated source of macro-financial vulnerability.

A timely recognition of the risks building up and of the dimensions of their systemic implications allows policy makers to tailor the intervention to the specific vulnerability, increasing the effectiveness of the available instruments. Intermediate policy objectives may vary; for example, increasing the resilience of the system through larger capital requirements, or dampening destabilizing speculative developments through the regulation of specific economic sectors. Analytical tools that capture the evolution of cyclical imbalances allow to map risks and thereby facilitate their targeting.

Established approaches to measure changes to macro-financial dynamics often rely solely on the univariate properties of credit measures (for example Borio et al.(2011)[13]). However, 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 build-up of macro-financial vulnerabilities. This is true particularly in a changing world in which the relationship between the financial system and the real economy is evolving. Also, conventional methods of estimating macro-financial imbalances through non-parametric filters have a number of inherent properties that might bias the trend-cycle decomposition. Such as the risk of obtaining spurious cycles due to the requirement to set the smoothing parameter and the frequency-bands upfront or a high trend persistency that risks to shadow cyclical turns (Hamilton(2017)[42] and Murray(2003)[66] provide a detailed discussion on the limitations of parametric filters to the estimation of cycles). The credit-to-GDP gap measure proposed by the Basel Committee on Banking Supervision (BCBS) as benchmark measure for countercyclical capital regulation, herein after Basel-gap, belongs to this sort of indicators.[1]

Our approach addresses these shortcomings by a method that incorporates relevant information beyond credit dynamics. We model the credit gap, as a latent stochastic cycle, through the joint behaviour of the lags of the cyclical component of the credit ratio and of a set of auxiliary variables. The main methodological contribution is to combine the fundamental aspects of the predominant methodologies while additionally allowing for a flexible inclusion or substitution of variables. Specifically, the relationship between

[1] 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 credit cycle.

the cyclical drivers of the credit-ratio and auxiliary variables is explicitly described by a set of equations that form a multivariate unobserved-components model. Additionally, this approach incorporates a time-varying structure in the errors of the unobserved and observed variables that form the state-space. This ensures that possible heteroskedastic error structures in the data generating process do not introduce spurious dynamics into the trend and the cycle estimates.

The paper is organised as follows: Section 2 reviews the relevant existing literature. Section 3 introduces the empirical model and provides details on the estimation method. Section 4 shows the perfomance of the filter through a Monte-Carlo experiment with simulated data. Details on the dataset used fot the empirical application are provided in Section 5. The results from the empirical model are presented in Section 6, including the role of real estate valuations and risk appetite shocks in the years prior to a banking crisis via a forecast error variance and historical decomposition analysis. Section 7 provides conclusions.

2 Related Literature

Despite its relevance in the policy field in the aftermath of the "Great Financial Crisis" (GFC) there is yet no unanimity in the definition of the financial cycle. Broadly, it is thought to synthesize whether the interactions between the financial sector and real economy are sustainable. Moreover, a substantial strand of literature has emerged building on the concepts outlined by Fisher(1933) "the business cycle, as a single, simple, self-generating cycle(...) is a myth", instead a number of cycles co-exist, constantly aggravating or neutralising each other, as well as coinciding with many non-cyclical forces (see Fisher(1933) p.338.[38]). This literature analyses the coincidence between credit, financial conditions and economic activity. A key finding is the link between credit intense boom periods, deep financial disruptions and slow recoveries (e.g. Claessens et al.(2012) [31], Jorda et al.(2011)[47] and Jorda(2011)[46] study the link between financial disruptions and deep economic recessions).

In that sense, equilibrium financial developments are often approximated by long-run credit trends or averages, while imbalances in macro-financial variables are characterized as self-reinforcing interactions between perceptions of value and risk, attitudes towards risk and financing constraints (see Borio (2014)[10]). Moreover, build-up phases of the financial cycle are considered to have good early warning properties for systemic banking crises and to have significant forecasting power signalling recession risk.[2][3]

[2]Applying standard turning point analysis to post-war data from advanced, euro area and developing economies Claessens et al.(2012)[31] and Hubrich et al. (2014)[53] find that large turning points in GDP coincide with those for financial series. Other studies approximate the cyclical dimension of systemic risk through the credit gap, for instance Borio and Lowe(2002)[16], Borio and Drehmann(2009)[12], Aldasoro, et al.(2018)[3] and Detken et al.(2014)[34].

[3]Borio et al.(2018)[15] finds that the financial cycle outperforms the term spreads in predicting recession risk.

Financial cycles are on average around four times longer and more ample than business cycles (see Gerdrup et al.(2013)[59], Detken et al.(2014)[34] and Galati et al.(2016)[58]). As asset prices are more volatile than economic fundamentals (Campbell and Glen(2003)[22]) financial cycles are often more pronounced than business cycles and downturns are deeper and more intense than recessions in economic activity. Claessens (2012)[31] finds that upturns tend to last longer than downturns. These asymmetries have implications for the sharpness of the cycle as the probability of reaching the peak during the upturn differs from the probability of trough in the downturn.

The lack of consensus on a specific definition of the financial cycle has lead to a large number of measurement techniques and approaches to illustrate the linkages between imbalances in the financial sector and large macroeconomic fluctuations. While univariate approaches rely entirely on the properties of the decomposed series, other methods synthesize multivariate information through structural time series models or by extracting common components in financial cycles (Schüler et al.(2015)[71]). Our approach combines both strands: we exploit the univariate properties of the credit ratio by decomposing it into its trend and cycle and, to inform the estimation of the cycle, capture multivariate information on macro-financial feedback loops through modelling the relationship between the credit cycle, asset prices and real economic activity.

The ease of the application of frequency based non-parametric filters has driven its popularity. Nonetheless, there are a number of important considerations and limitations related to their use, including the requirement of setting frequency bands and smoothing parameters upfront as it introduces a sense of arbitrariness into the results. This is well documented in the literature, for example Hamilton and Leff (2020)[49] puts into question the choice of the smoothing parameter of approaches that measure the credit gap with the H-P filter. Moreover, Murray (2003)[66] points out that frequency-bands chosen upfront carry the risk of obtaining spurious cycles, i.e. artificial boom and bust phases.

Common non-parametric approaches of trend-cycle decomposition are low- and band-pass filters. Low-pass filters, such as the Hodrick-Prescott filter (H-P) are suited to pick up the low-frequency movements attributed to the trend (e.g. Harvey and Trimbur (2003) [51]) Borio and Lowe (2002)[16] apply the H-P filter calibrating the smoothing parameter (λ) value to 400 000 in order to construct the credit gap as the difference between the actual and the trend level of the credit ratio. Besides the methodological shortcomings that reduce the reliability of its estimates, such as beginning and end-of sample biases and highly persistent trends, the H-P filter measure is the most prominent indicator of cyclical imbalances in policy applications.[4][5]

Bandpass filters are constructed to extract cycles with a stipulated length. Examples are the studies by Drehmann et al.(2012)[14] and Aikman et al. (2012)[4] that use a medium-term frequency band (32-120 quarters) to extract the financial cycle. WGEM (2018) apply the optimal asymmetric bandpass filter by Christiano and Fitzgerald(2003)[27] assuming a unit root with drift and defining the upper and lower boundary of the cycle length at 8-80 quarters. This statistical approach provides solutions to the end point problem. Nonetheless, establishing upfront the frequency bands might reduce the precision of the estimates as it conveys the risk of obtaining spurious cycles and of the failure of capturing relevant parts of cyclical dynamics (Murray (2003)[66] and Ruenstler et al.(2018)[70]).

The lack of substantive economic content of some univariate procedures might be reflective of their inability to capture the rich source of information stemming from different data sources. Structural empirical approaches such as unobserved-components (UC) models have been put forward for decomposing time series into permanent and transitory components (e.g. Watson(1986)[75], Clark(1987)[28], Harvey(1985)[50] or Hamilton (1988)[48]).[6] A major benefit of the state space formulation of unobserved components models is its flexibility as it allows to easily incorporate the relationships with additional variables and to tailor the model to the observed time series.

Forni et al.(2000)[56] describes economic activity in market economies as the alternation of up- and downturns which are characterized by the cyclical joint behaviour of several macroeconomic variables.[7] Building on the view that the business cycle embeds information of diverse time series Borio(2015)[11] extends univariate trend-cycle decomposition formulation by enriching the estimation of the cycle with financial factors and with the non-cyclical part of output. Recent research has applied this methods to the field of financial stability. Lang and Welz(2017)[61] and Galan and Mencia(2018)[57] estimate the credit-gap with a multivariate unobserved components filter.[8] Both approaches impose an explicit structure on the relation between the

[4]Following European Union (EU) legislation the credit-gap should serve as main reference to inform the buffer guide for the Countercyclical Buffer (CCyB) rate setting. This recommendation was issued by the European Systemic Risk Board (Recommendation ESRB/2014/1 following from the CRD IV package comprising EU Directive 2013/36/EU and EU Regulation 575/2013 introduced in 2013.

[5] Edge and Meisenzahl(2011)[36]) find that most of the revisions of the credit gap are related to the unreliability of end-of-sample estimates of the measure produced with the H-P filter rather than from revised values of the underlying data.

[6]UC models of trend cycle decomposition often imply a cycle that has a vast amplitude and is highly persistent and a very smooth trend, unlike the H-P filter or BN decomposition where most of the variation is attributed to the trend.

[7]This definition has its origins in the classical work by Burns and Mitchell(1946)[20] on the business cycle.

[8]While Lang and Welz(2017)[61] targets the identification of excessive credit developments for households, Galan and Mencia (2018)[57] looks at these imbalances at aggregate level and

trend component and the observable variables incorporating variables that embed an interpretation of the long-run equilibrium (for instance Albuquerque and Kurstev (2015)[2], Buncic and Melecky (2014)[19] and Juselius and Drehmann(2015)[55] model equilibrium credit through real estate prices and real output). In the fashion of dynamic factor models that exploit the strength of the relationship between the aggregate cycle and the cyclical components of individual time series our approach informs explicitly the estimation of the cyclical component by drawing on univariate trend-cycle decomposition models in a state space framework (for instance Clark(1987)[28], Harvey(1985)[50] and Hamilton(1988)[48]) as well as on its extensions to multivariate frameworks (e.g. Borio et al.(2015)[11], Azevedo (2011)[6] and Stock and Watson(2002)[73]).

Hubrich and Tetlow(2014)[44] finds that the linkages between financial stress and the macroeconomy display non-linear dynamics, therefore allowing for non linearities is key to avoid to bias the estimates that capture their interrelation.[9] The seminal work of Cogley and Sargent(2005)[33] and Primiceri(2005)[67] established a benchmark on the study of evolving interrelations between macroeconomic variables. The forecasting power of their time-varying parameter vector autoregression model (TVP-VAR) with stochastic volatility has been shown to outperform constant-coefficient counterparts in Clark(2009) [29], D'Agostino et al.(2013)[1] or Clark and Ravazzolo(2015)[30]. Sims and Zha(2006)[72] finds that the model that has the best data fit is one that allows for changes in the variances of structural disturbances. Moreover, Chan and Eisenstat(2018)[26], compares constant parameter vector autoregression (VAR) with homoskedastic innovations, constant parameter VAR models with stochastic volatilities and time-varying parameter VARs with stochastic volatilities through the models marginal likelihood and the deviance information criterion. The authors find that according to both criteria gains were derived from the incorporation of stochastic volatility. We account for non-linear dynamics by integrating a time-varying volatility structure into the trend-cycle decomposition filter. This model incorporates flexible error structures into the estimation of unobservable components extending hereby the stochastic volatility VAR. Our algorithm builds on Mumtaz(2010) [64] extension of a TVP-VAR model of dynamic volatility by an enlarged version of the factor augmented VAR (FAVAR) by Bernanke et al.(2005)[9].

3 Empirical Model

This section describes the structure of the decomposition model, the dynamics of the trend and the cycle components and the estimation procedure. The idea is that macro-

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allows for a contemporaneous relationship in the measurement equation between the cycle component and real estate prices.

[9] Hubrich and Tetlow(2014)[44] study whether there is empirical evidence for non-linearities in the linkages between the financial sector and macroeconomic dynamics by analysing whether the shifts in VAR coefficients and stochastic shocks coincide with those of established events in US economics and financial history. Additionally, this research finds that the linkages between financial stress and macroeconomic outcomes should be described by allowing for coefficient switching on top of a flexible variance structure.

financial dynamics are characterized by cyclical joint behaviour of economic aggregates. We integrate this notion by informing the estimation of the cycle through auxiliary variables. Time variation is introduced into the model by allowing for a drift in the error covariance matrix of the transition equation.

3.1 Unobserved components model of trend-cycle decomposition

We postulate that the target variable Θ_t will be decomposed into a stochastic trend and a stationary component (1).[10] Consistent with Harvey(1985)[50] the trend is modelled as a local approximation to a linear trend. The trend τ_t evolves as a random walk with a stochastic slope, which itself follows a random walk. The local and slope disturbances of the trend are mutually independent. In our specification the local disturbance of the trend evolves with stochastic volatility. The slope innovations φ_t follow a normal distribution.

$$\boldsymbol{\Theta_t = \tau_t + c_t} \tag{1}$$

$$\tau_t = \tau_{t-1} + \varphi_{t-1} + \upsilon_t \sqrt{exp(ln\lambda_t)}, \quad \upsilon_t \sim N(0,1) \tag{2}$$

$$ln(\lambda_t) = ln(\lambda_{t-1}) + \rho_t, \quad \rho_t \sim N(0, \sigma_\rho) \tag{3}$$

$$\varphi_t = \varphi_{t-1} + \xi_t, \quad \xi_t \sim N(0, \sigma_\xi) \tag{4}$$

The cyclical component c_t displays the stationary variation within the time series.[11] 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:

$$\begin{aligned} Z_t = BF_t + \nu_t, \quad \nu_t = A^{-1}\Lambda_t^{0.5}\epsilon_t, \quad \epsilon_t \sim N(0, I_N), \\ \Lambda_t = diag(\lambda_{1,t}, .., \lambda_{N,t}) \end{aligned} \tag{5}$$

$$ln(\lambda_{i,t}) = ln(\lambda_{i,t-1}) + \omega_{i,t}, \quad \omega_{i,t} \sim N(0, \sigma_\omega) \tag{6}$$

where $Z_t = [c_t, AX_{1t}, .., AX_{kt}]'$ is a $Nx1$ matrix of endogenous variables (for $i = 1, .., N$ model variables of which $k = 1, .., K$ are auxiliary variables). $F_t = [Z'_{t-1}, .., Z'_{t-p}, 1]'$ denotes the $Nx(NP+1)$ matrix of endogenous variables and B is the $Nx(NP+1)$ matrix of coefficients $B = [B_1, ..., B_{Pt}, \mu_t]$.

A is a lower triangular matrix with ones on the main diagonal and coefficients a_{qj} in row q and column j (for $q = 2, .., N$, $j = 1, .., i-1$) and Λ_t is a diagonal matrix which

[10] In our application the target variable will be the credit ratio , $y_t = CreditRatio_t$.

[11] 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)[50] or Clark(1987)[28].

contains the stochastic volatilities. As in (3) these evolve as geometric 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)[33]. As Carriero et al.(2016)[23] we don't allow the elements in A^{-1} to vary over time. The reason for this choice is that Primiceri(2005)[67] found little variation in those coefficients and the specification of the variation in these coefficients would require the estimation of additional $N(N-1)/2$ equations.

The reduced from VAR innovation ν_t time-varying covariance matrix is factored as (7).

$$VAR(\nu_t) \equiv \Sigma_t = A^{-1}\Lambda_t(A^{-1})' \tag{7}$$

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 (8) describes the dynamics within the state space taking as example the case k=2.

$$\begin{bmatrix} \tau_t \\ c_t \\ AX_{1t} \\ AX_{2t} \\ c_{t-1} \\ AX_{1t-1} \\ AX_{2t-1} \\ \varphi_t \end{bmatrix} = \begin{bmatrix} 0 \\ \mu_1 \\ \mu_2 \\ \mu_3 \\ 0 \\ \vdots \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & \cdots & \cdots & \cdots & \cdots & 1 \\ 0 & b_{11} & b_{12} & b_{13} & b_{14} & b_{15} & b_{16} & \vdots \\ \vdots & b_{21} & b_{22} & b_{23} & b_{24} & b_{25} & b_{26} & \vdots \\ \vdots & b_{31} & b_{32} & b_{33} & b_{34} & b_{35} & b_{36} & \vdots \\ \vdots & 1 & 0 & \cdots & \cdots & \cdots & \cdots & \vdots \\ \vdots & 0 & 1 & 0 & \cdots & \cdots & \cdots & \vdots \\ \vdots & \cdots & \cdots & 1 & 0 & \cdots & \cdots & 0 \\ 0 & \cdots & \cdots & 0 & \cdots & 0 & \cdots & 1 \end{bmatrix} \begin{bmatrix} \tau_{t-1} \\ c_{t-1} \\ AX_{1t-1} \\ AX_{2t-1} \\ c_{t-2} \\ AX_{1t-2} \\ AX_{2t-2} \\ \varphi_{t-1} \end{bmatrix} + \begin{bmatrix} e_t^{\tau} \\ \nu_{1t} \\ \nu_{2t} \\ \nu_{3t} \\ \vdots \\ 0 \\ e_t^{\varphi} \end{bmatrix} \tag{8}$$

(9) represents the measurement equation that relates unobserved variables and observable variables.

$$\begin{bmatrix} \Theta_t \\ AX_{1t} \\ AX_{2t} \end{bmatrix} = \begin{bmatrix} 1 & 1 & \cdots & \cdots & \cdots & \cdots & 0 \\ 0 & 0 & 1 & 0 & \cdots & \cdots & 0 \\ 0 & 0 & 0 & 1 & 0 & \cdots & 0 \end{bmatrix} \begin{bmatrix} \tau_t \\ c_t \\ AX_{1t} \\ AX_{2t} \\ c_{t-1} \\ AX_{1t-1} \\ AX_{2t-1} \\ \varphi_t \end{bmatrix} \tag{9}$$

3.2 Estimation

We estimate the model using a Metropolis-within-Gibbs algorithm. In this section, we summarize the estimation algorithm. Appendix A, B contain further details on the prior distributions and sampling method. The Gibbs sampler cycles through the following steps:

1. Set starting values.

2. Conditional on a draw of the unobserved components [12] A, Λ_t, and Ω sample VAR coefficients from a normal posterior distribution.[13]

3. Conditional on the draw of the VAR coefficients in step 2. compute the VAR residuals v_{it}.

4. Draw the time invariant a_{ij} elements of the VAR-COV matrix with a heteroscedastic linear regression as in Cogley and Sargent(2005)[33].[14]

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)[54].

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-Kohn(1994)[24] algorithm to cast the unobserved components in a state space model as in Mumtaz(2010)[64].

9. Go to step 1.

4 Estimation using simulated data

We perform a simulation exercise to test the performance of the algorithm. We generate 220 observations from a data generating process that is divided into 2 steps. First, we model the stationary cycle component, auxiliary variables and trend. In a second step, we generate the target variable as a sum of the cycle and the trend. For k=2 and p=2 we generate three series: the cycle and two auxiliary variables from the following process:

$$Z_t = BX_t + A^{-1}\Lambda_t^{0.5}\epsilon_t, \;\; \epsilon_t \sim N(0, I_3) \tag{10}$$

where Z_t is 3x1. B and A are fixed.

In line with Ruenstler and Vlekke(2016)[69] we characterize the credit cycle as a persistent process. Moreover, for this experiment we set values for the beta parameters

[12]We start the algorithm with a bandpass- cycle extraction calibrated to approximate the financial cycle as in Claessens (2012)[31]

[13]The vector of coefficients is drawn from a posterior distribution with mean and variance as in Clark(2009)[29].

[14]As in Cogley and Sargent(2005)[33] 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. Given, the Cholesky-type structure of the A matrix that allows to estimate Σ_t as in (7) it seems that the order of the variables matter. This 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 irrelevant.

such that the auxiliary variables are a relevant source driving the and cyclical dynamics. The elements of the time-varying diagonal matrix Λ_t evolve as:

$$ln(\lambda_t^z) = ln(\lambda_{t-1}^z) \ + Chol(Q)\, \eta_t^z, \ \ Q = I_N \, x \, 0.1, \ \ \eta_t^z \sim N(0, I_N) \tag{11}$$

In parallel, we generate the series for the trend as

$$\tau_t = \tau_{t-1} + \varphi_{t-1} + \upsilon_t \sqrt{exp(ln\lambda_t^\tau)} \ \ \upsilon_t \sim N(0,1) \tag{12}$$

$$ln(\lambda_t^\tau) = ln(\lambda_{t-1}^\tau) \ + \ 0.001^{0.5} \eta_t^\tau, \ \ \eta_t^\tau \sim N(0,1) \tag{13}$$

$$\varphi_t = \varphi_{t-1} + 0.001^{0.5} \eta_t^\varphi, \ \ \eta_t^\varphi \sim N(0,1) \tag{14}$$

We then generate the target variable Θ as the sum of c and τ. As motivated in the introduction, in our model the credit cycle is approximated by a measure of the interrelation of aggregates reflective of macroeconomic imbalances. Our fictitious dataset replicates this two-sided relationship between the state variable of the cycle and the auxiliary variables.

The experiment is repeated 500 times producing at each iteration a new data set. The state-variables are kept constant for the stochastic volatilities, static VAR parameters and covariance parameters.

We estimate the model with loose priors 500 times, i.e. once for each dataset. We use 40 observations as training sample. This leaves 180 observations for the estimation. The model estimation uses 15000 Gibbs iterations with a burn-in of 14500 iterations.

Figure 1 displays the estimated median trend and cycle and error bands against its true value for a single simulated series. The good tracking of the original series by the median estimate and thin error provides evidence that the algorithm proposed in this paper is an appropriate tool to capture trends and cycles in a changing environment. Figure 11 displys the posterior distribution of the estimated beta parameters against the real values.[15] The estimated beta values are on average closer to the true values in the last two rows, that is for the auxiliary variables, than in the first row that contains the relation between the cycle component and the other parameters. Nevertheless, the slight divergences from the true parameter values do not hamper the performance of filter to identify the true trend and cycle components, as shown in Figure 1.

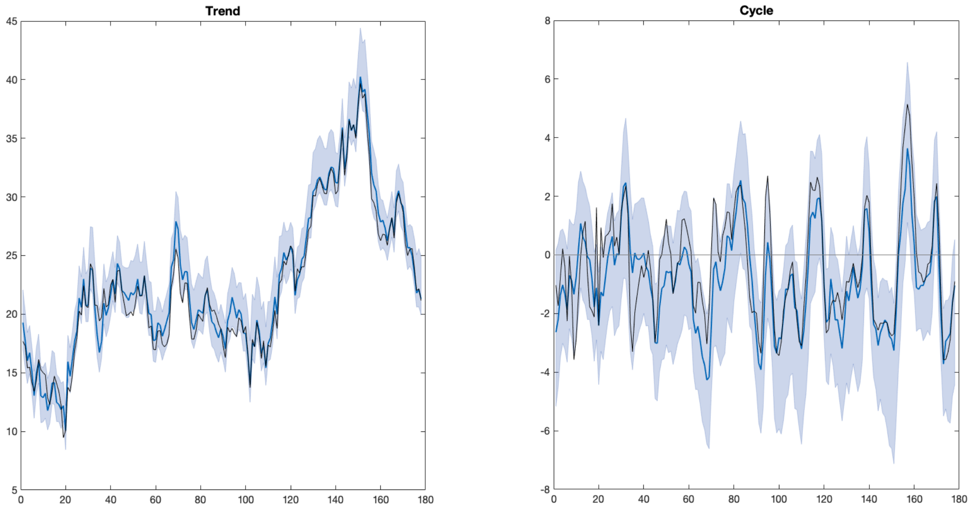
5 Data

In this application the target variable is the credit ratio. We include this variable in levels in order to retain the information contained in the trend. The auxiliary variables contribute to estimate the cyclical component. These reflect deviations from equilibrium developments for each single variable. Table 2 provides details on the data sources and performed transformations. The credit ratio series used in this study is compiled by the BIS.[16] Beyond displaying the relative growth of credit with respect to GDP, indicators

[15] Figure C displays the distribution of the estimated covariance parameters.

[16] Due to increased financial deepening and liberalisation in the aftermath of the second world war credit growth was stronger than changes in GDP. For that reason the credit-ratios of most developed countries which are tilted upwards after 1945 (Aikman et al.(2015)[4])

FIGURE 1. The thick blue line represents the median estimated trend-cycle decomposition and the shaded area represents the 68% error band. The black lines represent the true values.



developed from the credit ratio were found to have a good properties to signal banking system distress both on a stand alone basis or in combination with additional measures such asset price gaps (e.g. Borio(2012)[14] and Borio and Lowe(2002, 2004)[16],[17]). The drivers of unsustainable credit developments and the weight of their individual contribution to cyclical risk change dynamically. 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. Therefore it is key to capture the cyclical joint behaviour of diverse variables reflective of the build-up of cyclical vulnerabilities in the financial system.

As boom-bust cycles in real estate prices, both residential and commercial, are considered fundamental sources of financial fragility, we will assess valuation pressures in the mortgage market through the price-to-income ratio relative to a 10-year moving average. Subtracting the long-run average we minimize the influence of structural drivers. Deviations from the long-term trend represent a measure of housing market valuations related imbalances. We construct this measure following Cecchetti(2008)[25] and Rogoff and Reinhart(2010)[68]. It should be noted that this approach carries the implication that trend changes represent benign developments in the context of financial system vulnerabilities.[17] 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)[31]; Schuler et al.(2015)[71]; Galati et al. (2016)[58] and Ruenstler and Vlekke(2016)[69]).

[17] This issue was raised by Aikman et al.(2015)[4].

Financial conditions refer to the state and functioning of financial markets that affect economic behaviour and consequently the current and future state of the economy. Moreover, measures of financial conditions have been shown to be reliable predictors of economic activity. We include this risk channel through a measure that captures the state of financial conditions and thereby reflects financial sector risk (e.g. Guichard, Haugh and Turner (2009)[41], Hatzius et al. (2010)[52] and Wacker et al.(2014)[74]). For the US the second auxiliary variable is the Excess Bond Premium (EBP) as in Gilchrist and Zakrajsek(2012)[40]. 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. Also, this indicator is considered to be a good measure to signal an increase in the probability to enter an economic recession.[18] Arregui et al.(2018)[5] finds that corporate spreads and equity return volatility are amongst the financial variables that most contribute to countries' financial conditions. As the second auxiliary variable for the United Kingdom we include corporate spreads. For Ireland we construct a measure of equity volatility through the realised monthly volatility in the equity index.

Periods of low risk can be conducive of a greater build-up of systemic risk through higher levels of leverage. This phenomenon was denominated by Brunnermeier and Sannikov(2014)[18] as the volatility paradox. In line with this literature low values of the auxiliary variable that reflects financial sector risk should contribute positively to increases in the credit-cycle. We therefore include the second variable with a negative sign in the model. Through this transformation a spike in this series will be reflective of a materialisation of risk and push the credit cycle downwards.

Rapid decreases in unemployment are often interpreted as a sign of economic overheating. In order to capture the build-up 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 credit cycle, therefore this variable will enter the model with a negative sign.

6 Empirical Results

This section presents the results of the country level estimates for the financial cycle for the US, the UK and Ireland. Model selection is performed based on the models' log-scores (LS). For the three countries the credit cycle moves in accord with the crisis episodes documented by in Drehmann and Juselius(2014)[35] and is characterized by a strong persistence. To get an insight of the main drivers of the credit cycle, the following functions of the VAR coefficients are reported: forecast error variance decomposition and historical decomposition.

[18] For the years where no EBP is available we proxy the measure through the difference between Moodys seasoned BAA corporate and the Fed funds rate.

TABLE 1. Four-periods ahead predictive log-scores (LS) averaged.Ordered by descending levels of prior tightness for the target measure.

	Prior tightness (τ)							
	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US	-7.583	-6.430	-6.198	-6.460	-6.130	-5.1378	-5.484	-4.806
UK	-8.570	-8.485	-5.828	-5.293	-4.752	-4.409	-4.680	-4.345
IE	-4.128	-4.468	-5.263	-5.210	-5.152	-5.797	-4.945	-8.678

6.1 Model selection

Following Geweke and Amisano(2010)[39] we compare different levels of prior tightness based on the predictive density of the target variable Θ. Scoring rules evaluate the accuracy of the predictive densities by assigning a numerical score based on the forecast and the subsequent realisation of the variable (for more information on this procedure refer to Mitchell and Wallis (2011)). Concretely, for each level of prior tightness τ we compute:

$$log\ p(\Theta_{iT}|\Theta_{iS},\tau) = \sum_{t=S+1}^{T} log\ p(\Theta_{it+h}|\Theta_{it}) \tag{15}$$

where τ takes values between 0.2 and 0.9[19], 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 $t = S+1, ..T$ is the evaluation period for $S < T$. The evaluation period is the last ten years of the sample (2009:Q1 to 2019:Q1). Table 1 shows the 1 year ahead log-scores, i.e. $h = 4$, for each country model. On this basis we select the following values: $\tau = 0.9$ for the US, $\tau = 0.9$ for the UK and $\tau = 0.2$ for Ireland. As in Banbura et al.(2010)[7], the sum of coefficients prior is set as $\lambda = 10\tau$. This reflects loose prior beliefs and is proportional to the overall tightness parameter τ selected based on Table 1, that maximizes the forecasting accuracy of the model. Finally we set a tight prior on the constants such that, for its better interpretation and comparability, the cycle oscilates around the x-axis.[20]

6.2 Estimates of the credit cycle

Figures 2-4 display the estimated credit-cycle for the US, the UK and Ireland.[21] The red line shows the median of its posterior distribution and the shaded area represents the 68% error band and the blue line displays the Basel-gap. Overall, the fluctuations of the credit cycle can be divided into two stages: upward tendencies can be interpreted as build-up in the level of macro-financial imbalances, while downward trajectories

[19]Based on the values commonly used in the literature, see Canova(2007)[21], 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, i.e. $\tau = 0.1$ 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.

[20]See Appendix A.2 for more details on the prior parameters.

[21]Appendix D.1 displays the estimated trend.

can be read as periods of risk materialization or dissipation. Based on Drehmann and Juselius(2014)[35] the sample covers two banking crisis: 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.

Similar to other indicators of cyclical risk such as the Basel-gap, our estimate for the US 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 credit-cycle peaks already four quarters ahead of the GFC, while the Basel-gap reaches its maximum value one quarter past the crisis outbreak, i.e. 2007Q4. This property is indicative of a superior early warning capacity of the credit-cycle with respect to the Basel-gap. In the periods following the GFC the decay of the credit-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 credit 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 the US, the credit cycle peaks ahead of the Basel-gap prior to the GFC. Also, in the UK the credit-cycle displays a less persistent downturn during the recovery period than the HP estimate. In Drehmann and Juselius(2014)[35] the GFC, starting in 2008Q4, is listed as the unique banking crisis episode for Ireland. As displayed in Figure 4 our measure of the credit cycle peaks ahead of the Basel gap prior to that crisis episode. Also, it reverses its downward trajectory along the economic recovery mid-2013, while the Basel-gap remains on its downward path till the end of 2018.

Building on the application of the proposed method to three economies, we find that our proposed estimate of the credit-cycle signals the increase in systemic risk prior to past banking crises earlier than the Basel-gap. Moreover, the credit-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.

FIGURE 2. Credit cycle for the US 1971:Q3-2019:Q1.

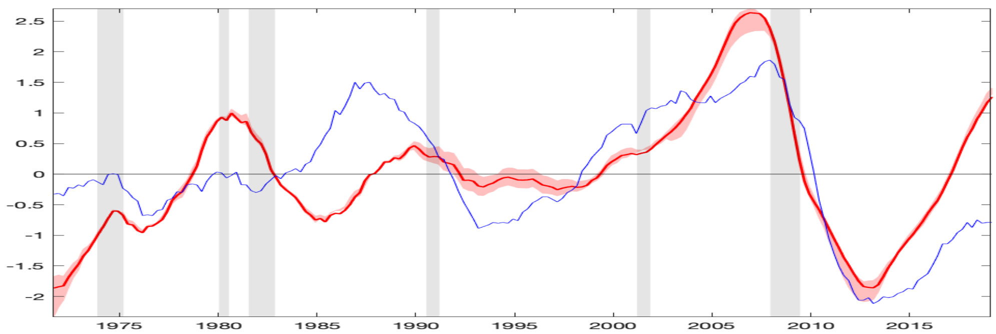


FIGURE 3. Credit cycle for the UK 1973:Q4-2019:Q1.

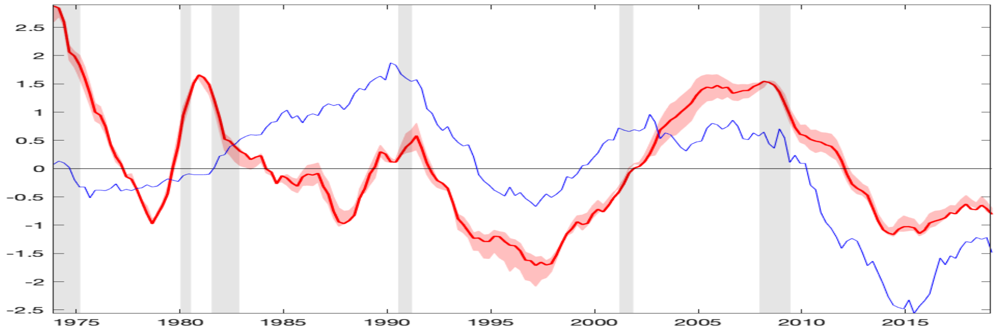
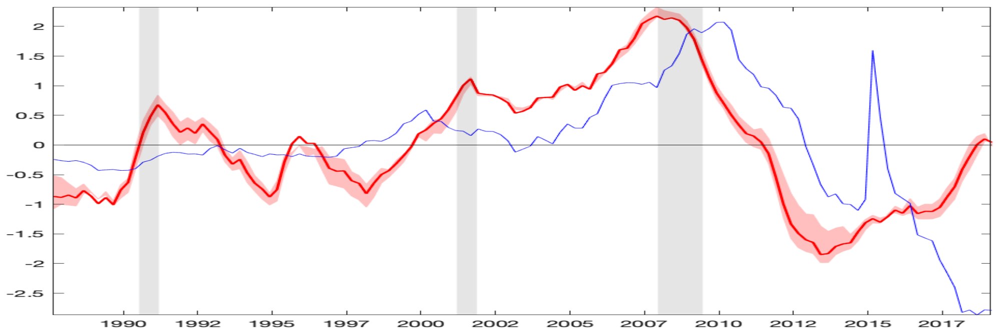


FIGURE 4. Credit cycle for Ireland 1987:Q3-2019:Q1.



The red line shows the standardized median estimated cycle from the decomposition. The shaded area represents the 68% error band. The blue line displays the standardized Basel-gap (BIS). Grey area represents the NBER economic recessions.

6.3 Forecast error variance decomposition

The time varying forecast error variance decomposition of the credit cycle for the US, the UK and Ireland is shown in Figure 5-7. Note that the X-axis represents the time-periods while the Y-axis is the contribution to the forecast error variance at a short term horizon of 2 years in the LHS and a medium term horizon of 5 years in the RHS.

The forecast error variance decomposition at every point in time are computed using the estimated (non-dynamic) parameters and the volatilities corresponding to these points in time and describes in absolute terms which shock is more important in driving the realisation away from the forecast.[22] It should be noted that the Cholesky-type decomposition that allows to estimate Σ_t as in equation (7) 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

[22]The autoregressive component of the credit cycle is ordered as the first variable in the Cholesky decomposition, therefore its contribution decreases at horizon 8 (RHS).

parameters such as those presented in the in this section and subsection 6.4 are reduced form estimates and only indicative of underlying structural relationships.

At a medium term horizon the housing market valuations shock proxied through the deviations from long run averages in the house-price to income ratio is the variable that contributes the most to the forecast error variance decomposition of the credit cycle of the US and also of the UK. During the pre-crisis periods explaining around 60% in the late 80s and up to 90% in the US 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 US during the "savings and loans crisis" 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 US the contribution of unemployment amounted to about 35% in the years surrounding the economic recession that started at 1973.

Shocks to real estate valuations explain around 20% of the error variance decomposition of the credit cycle for Ireland from 1987:Q3 to 2019:Q1. While in the two years after the GFC the shock to deviations in unemployment explains uo to 30% of the forecast error variance decomposition. The contribution of the own lags of the credit cycle in the FEVDC of the Irish credit cycle is larger than for the other two country models. It should be noted that in the Irish model the prior maximizing the forecasting accuracy is tighter than for the US and the UK, putting more weight on the own lags of the cycle.[23]

6.4 Historical decomposition

The historical decomposition 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 trend 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 credit cycle.

Figure 8 shows the results for the de-trended median posterior estimate for the US credit-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.[24] Hence decreases in the EBP contributed positively to the build-up 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 (see Brunnemeier and Sannikov(2014)[18]).

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 credit cycle. The decompositions also demonstrate that the increase in the cycle after

[23] See section 6.1 on prior selection based on the predictive density.

[24] For its interpretation it should be beard in mind that this variable enters the model with a negative sign.

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 credit cycle increased over time as these shocks have played a much smaller role in times prior to 2005 than afterwards.

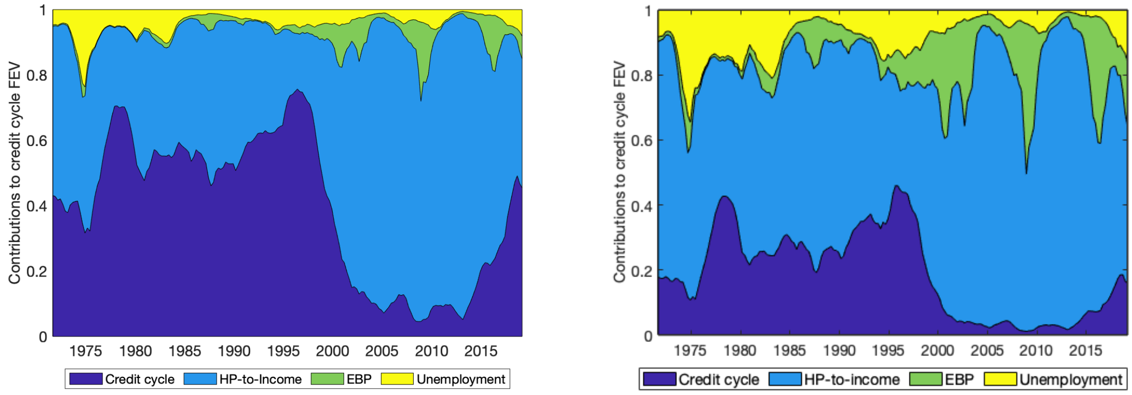
The historical decomposition of the UK credit cycle in Figure 9 displays how between 1990 and 2010 shocks to real estate valuations were the main sources of deviations of the credit cycle from its baseline path in the UK. Between 2012 and 2019:Q1 shocks to financial conditions represented by the credit spread were the main drivers of the credit cycle away from its expected path.

The historical decomposition for the de-trended credit cycle for Ireland in Figure 10 shows that shocks to financial conditions, proxied by the shock on return on equity, contributed negatively to the credit cycle particularly in the years after the GFC. In line with the results for the US and the UK real estate valuations shocks contributed positively to the credit cycle in the years prior to the GFC. While after 2008 the contribution of the real estate valuation shocks was negative. Moreover, between 2018:Q3 and 2019:Q1 negative shocks to real estate valuations were the most important driver of the credit cycle away from the baseline forecast, while the contribution of shocks to financial conditions diminished.

Appendix D.2 contains the median estimates for the stochastic volatilities of the latent and observable variables. For the US, the UK and Ireland the stochastic volatility of the trend changed at a faster pace after 2000. This goes in line with the estimated trend (Figure 13) that seems to be moving faster in recent times. On the other hand the cyclical movements were faster before the 1980s for the US and the UK.[25] This finding supports the literature that associates the Great Moderation period, starting from the mid-1980s, with a lower volatility (e.g. McConnell and Perez-Quiros(2000)[62], Cogley and Sargent(2005)[33] or Primiceri(2005)[67]).

[25] This cannot be observed for Ireland due to the shorter sample.

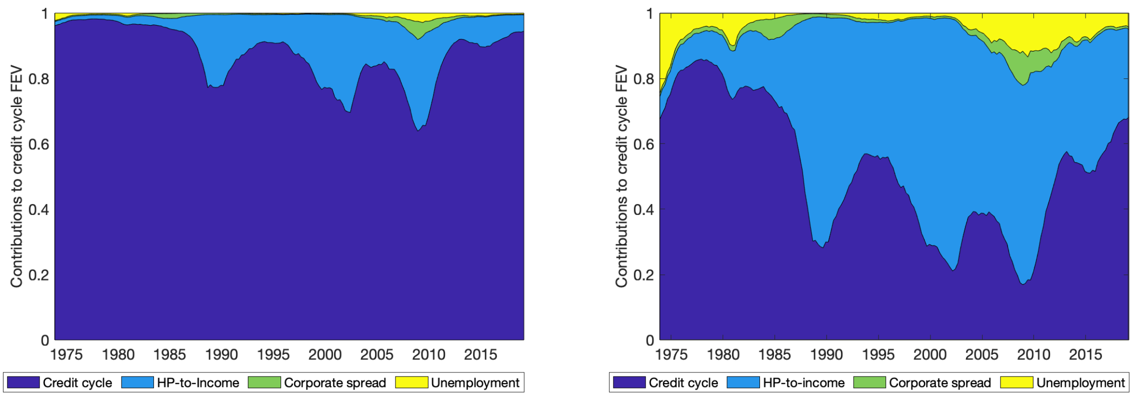
FIGURE 5. Forecast error variance decomposition US credit cycle 1971:Q3-2019:Q1



Short term horizon of 2 years

Medium term horizon of 5 years

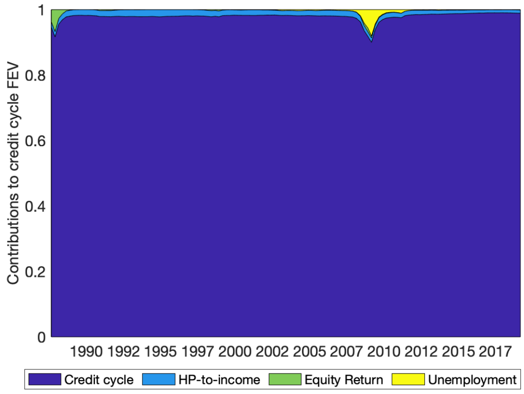
FIGURE 6. Forecast error variance decomposition UK credit cycle 1973:Q4-2019:Q1



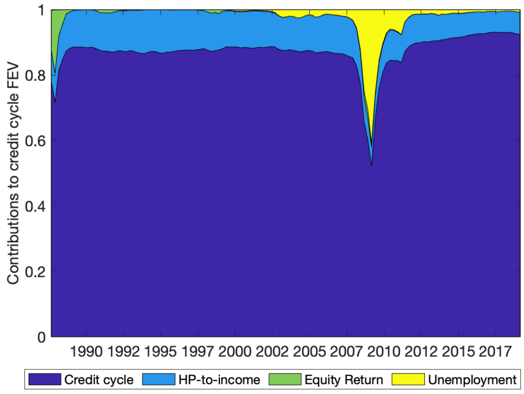
Short term horizon of 2 years

Medium term horizon of 5 years

FIGURE 7. Forecast error variance decomposition Ireland credit cycle 1987:Q3-2019:Q1



Short term horizon of 2 years



Medium term horizon of 5 years

FIGURE 8. Historical Decomposition US credit cycle 1971:Q3-2019:Q1

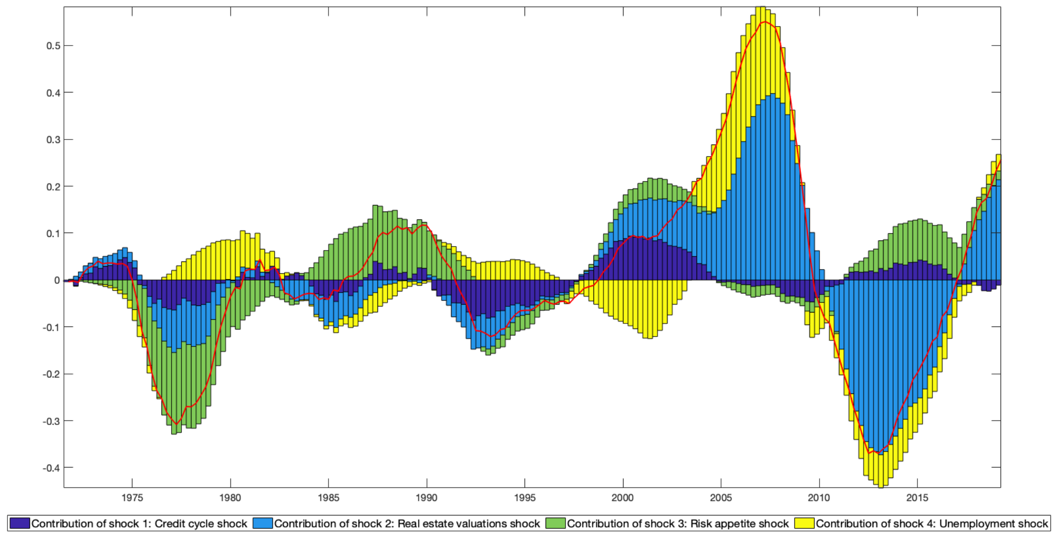


FIGURE 9. Historical Decomposition UK credit cycle 1973:Q4-2019:Q1

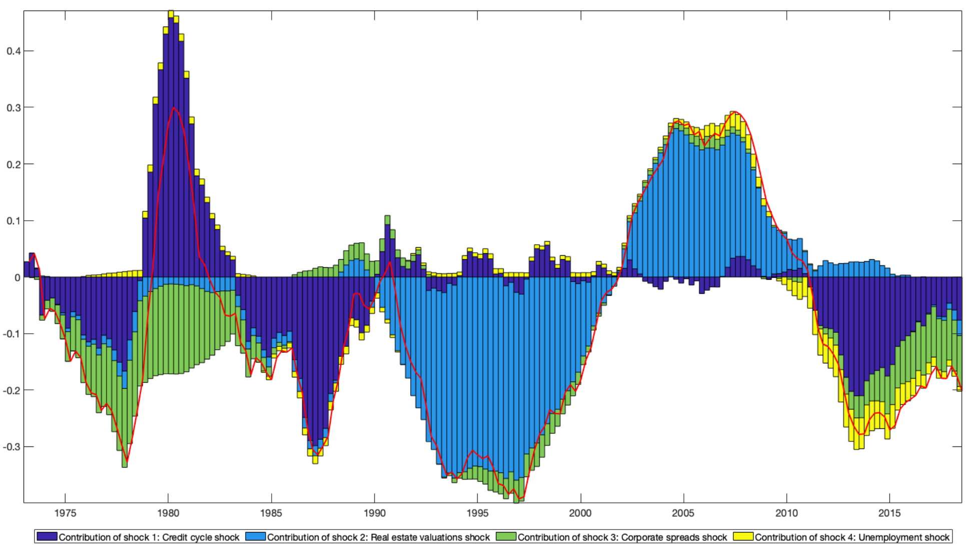
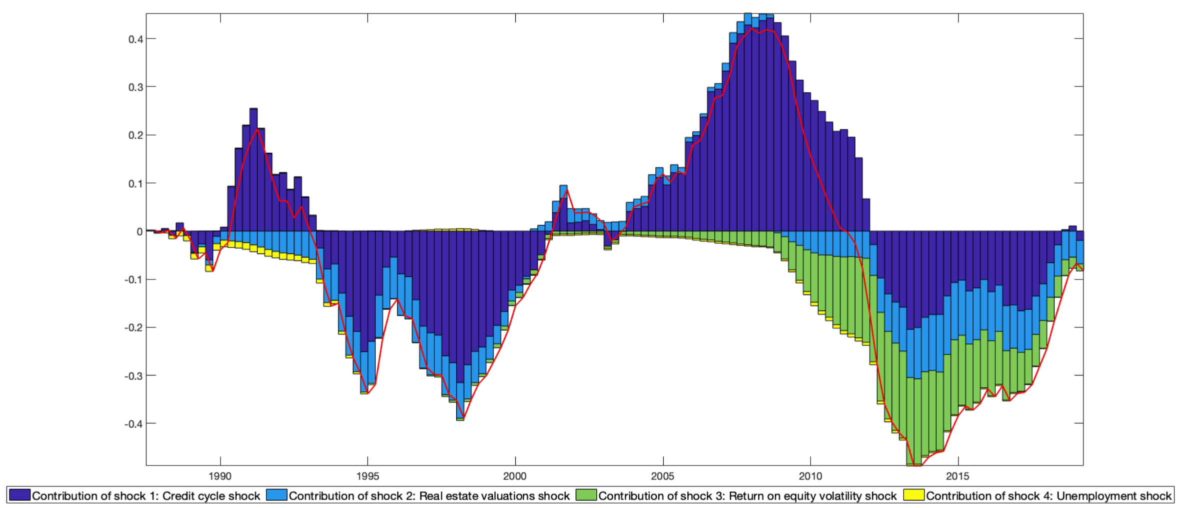


FIGURE 10. Historical Decomposition Ireland credit cycle 1987:Q3-2019:Q1



Red line represents the de-trended median posterior estimate

7 Conclusion

The GFC has raised new challenges for policy makers, 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, a highly persistent trend or an upfront selected smoothing parameter reduces its precision in measuring the build-up 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 the model to the US, the UK and Ireland and find that including information beyond the univariate properties of credit, by explicitly modelling the joint dynamics of the observed and latent dynamic variables in the state space, our measure provides more informative estimates of the financial cycle as those provided by frequency based filters. In particular, the empirical results characterise the patterns distinguishing previous crises: whereas changes in the financial conditions increased macro-financial vulnerabilities in the period prior to the SLC, changes in household vulnerabilities were the main factor in the years prior to the GFC. Moreover, in line with the Great Moderation literature, the estimated volatility of the cyclical component in the credit ratio for the US and the UK decreased in the 1980s.

Based on data up to 2019:Q1, we find a positive credit cycle for the US. Similar to the period preceding the GFC, we find building risks associated with housing market valuation issues. For the UK and Ireland we find that the credit cycle is on an upward trajectory at a faster pace than indicated by the Basel-gap. While our results point in that direction, further analysis of the distributional aspects, both geographical and by income level, would help refine this assessment. Measures aimed at increasing household resilience, such as borrower-based measures, could be explored.

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Appendix

The Gibbs sampling algorithm

A Priors

The prior distributions for the initial values of the states B_0, α_0 and h_0 are postulated to be normal and are assumed to be independent of one another. The independence assumption also holds for the distribution of the hyper parameters.

A.1 Unobserved components

The initial states of the trend and cycle components of $F_{0/0}$ are set using a bandpass filter with a passband frequency range specified between 8 and 32. In order to reflect the uncertainty surrounding the choice of starting values, a large prior covariance of the states $P_{0/0}$ is assumed.

A.2 Priors on the VAR parameters

Following Banbura et al. (2010) [7] we introduce natural conjugate prior for the VAR parameters via dummy observations. We choose the prior means μ_n as OLS estimates of the coefficients of an AR(1) regression estimated for each endogenous variable using a training sample consisting of the 40 first observations. These are removed from the sample afterwards. The scaling factors σ_n are set using the standard deviation of the error terms from these preliminary AR(1) regressions. Here τ reflects the degree of shrinkage which is higher the closer it is to 0. We set the overall prior tightness τ based on the highest models' LS for the target variable. We report the results for the examined grid of τ in Table 1. We set $c = 1000$ indicating a tight prior on the constant.

Doan, Litterman, and Sims (1984) and Litterman (1986a) proposed this priors through the application of methods of Bayesian shrinkage. We implement the Normal Inverted Wishart prior through Dummy observations as in Eq.(16). These are set such that the moments of the Minnesota prior are matched. In that sense the prior variance decreases with increasing lag length, carrying the belief that more recent lags contain more relevant information.

$$Y_{D,1} = \begin{pmatrix} \frac{diag(\sigma_1\mu_1,\ldots,\sigma_N\mu_N)}{\tau} \\ 0_{Nx(P-1)xN} \\ \ldots\ldots\ldots \\ diag(\sigma_1\ldots.\sigma_N) \\ \ldots\ldots\ldots \\ 0_{1xN} \end{pmatrix}, \; and \;\; X_{D,1} = \begin{pmatrix} \frac{J_P \otimes diag(\sigma_1,\ldots,\sigma_N)}{\tau} 0_{NPx1} \\ 0_{NxNP} \; 0_{Nx1} \\ \ldots\ldots\ldots \\ 0_{1xNP} \;\; c \end{pmatrix} \tag{16}$$

$$X_D = ((1 \;\; 2...p) \otimes diag(\delta_1\mu_1, ..., \delta_n\mu_n)/\tau)0_{nx1})$$

Additionally, for those variables that have a unit root we impose a sum of coefficients prior. This is a modification of the Minnesota prior suggested by Litterman (1986a) and carries the belief, that the sum of the coefficients of the lags equates to 1 (Robertson and Tallman (1999)).The tightness of the sum of coefficients prior is set as in Banbura et al.(2010) $\lambda = 10\tau$ and is introduced by adding the following dummy observations:

$$Y_{D,2} = \left(\frac{diag(\sigma_1\mu_1, ..., \sigma_N\mu_N)}{\lambda}\right) \tag{17}$$
$$X_{D,2} = \left(\frac{(1 \;\; 2...p) \otimes diag(\sigma_1\mu_1, ..., \sigma_N\mu_N)}{\lambda} 0_{nx1}\right)$$

A.3 Priors on covariance parameters

As to calibrate the prior distribution of α_0 we run a time-invariant VAR including on the auxiliary variables. This is based on the training sample. $\hat{\Sigma_0}$ is the estimated covariance matrix of the residuals ϵ_t. As in Benati and Mumtaz (2007)[8] let C be the lower-triangular Choleski factor of $\hat{\Sigma_0}$ such that C'C= $\hat{\Sigma_0}$ and $C = \hat{\Sigma_0^{\frac{1}{2}}}$. The estimated matrix $\hat{C_0}$ is computed by dividing each column of C by the corresponding element of the diagonal. Through this transformation the elements outside the main diagonal are normalized. After computing the inverse of $\hat{C}$ the elements below the main diagonal of $\hat{C_0^{-1}}$ are collected (i.e.all non-zero and non-one entries). This values will be set as the starting values of α in the vector $\tilde{\alpha_0} \equiv [\alpha_{0,21}, \alpha_{0,31}, \alpha_{0,32}]$.

A normal prior is assumed for the regression coefficients in each equation, as in equation(18). The conditional posterior distribution of α_i in eq.(19) is also assumed to be normal. Here Z_i are the left-hand variables and z_i right-hand variables transformed proportional to the variance of the structural shocks for the weighted regressions in section B.2). As in Mumtaz and Theodoris (2017)[65] $\underline{V_{i0}}$ is assumed to be diagonal with its elements set equal to 10 times the absolute value of the corresponding element of $\underline{\alpha_{i0}}$.

$$\alpha_{i0} \sim N(\underline{\alpha_{i0}}, \underline{V_{i0}}), \;\; i = 2, 3 \tag{18}$$

$$\alpha_i | B, H_i^T, Y^T \sim N(\overline{\alpha_i}, \overline{V_i}), \;\; i = 2, 3 \tag{19}$$

Where

$$\overline{V_i} = (\underline{V_{i0}^{-1}} + Z_i' Z_i)^{-1}, \tag{20}$$

$$\overline{\alpha_i} = (\underline{V_{i0}^{-1}}\underline{\alpha_{i0}} + Z_i' z_i) \tag{21}$$

A.4 Priors of the idiosyncratic shock volatility transition equation of the cyclical dynamics

The prior for the diagonal elements of the covariance matrix Λ, see equation (6) as in Ellis et al. (2014)[37] it is assumed to be normal, with μ_0^z set as the logs of diagonal elements of the Cholesky decomposition of $\hat{\Sigma_0}$ and $\sigma_0^z = 10$.

$$ln(\lambda^z) \sim N(\mu_0, \sigma_0) \tag{22}$$

An inverse Gamma prior is set for σ_ω with $g_0 = 0.01^2$ and $\nu_0 = 1$.

$$p(\sigma_\omega) \sim IG(g_0, \nu_0) \tag{23}$$

A.5 Priors on the disturbance parameters of the slope innovations

The variance of the slope innovations are simulated from an inverse gamma 2 (IG_2) distribution. Where the IG_2 is re-parametrised in terms if the mean and variance. Taking the two first moments Inverse Gamma-2 distribution as in Bauwens et al. (1999) and solving for gamma parameters allows to calibrate the scale parameter g_0 and degrees of freedom d_0 of the prior given values for the mean and the variance. The prior (24) and posterior(25) distribution of σ_ξ may be represented as

$$\sigma_\xi^2 \sim \quad IG_2(\sigma_0^\xi,\ \nu_0^\xi) \tag{24}$$

$$\sigma_\xi \sim \quad IG(\frac{g_1}{2}, \frac{d_1}{2}) \tag{25}$$

With g_1 and d_1 defined as

$$g_1 = g_0 + T \tag{26}$$

$$d_1 = d_0 + (\varphi_t - \varphi_{t-1})'(\varphi_t - \varphi_{t-1}) \tag{27}$$

We set a loose prior $\sigma_\xi \sim IG_2(0.001, 1)$. The mean is consistent with Ruenstler and Vlekke (2017)[69] that fixes the standard deviations of slope innovations to credit volumes to 0.001 for most of the countries in their sample.

A.6 Priors of the idiosyncratic shock volatility transition equation for the trend

The prior for the stochastic volatilities for the trend (eq.) is normal with μ_0^τ set as the logs of the standard deviation of the first difference of the pre-sample estimate of the trend and $\sigma_0^\tau = 10$. An inverse Gamma prior is set for σ_ρ with $g_0 = 0.01^2$ and $\nu_0 = 1$.

$$ln(\lambda_0^\tau) \sim N(\mu_0, \sigma_0) \tag{28}$$

$$p(\sigma_\rho) \sim IG(g_0, \nu_0) \tag{29}$$

B Sampling from the Posterior Density

The model is estimated using a Metropolis-within-Gibbs sampler. This methodology was developed in Cogley and Sargent (2005) for VAR models and by Primiceri (2005) for state space models. The volatilities of the reduced form shocks H_t are drawn using the date by date blocking scheme introduced in Jacquier et al.(2002) wich assumes that the stochastic volatilities are independent.

This procedure is reduced into five blocks. The first involves sampling the VAR parameters β^T that relate the cycle and the auxiliary variables. The second block involves the estimation of the covariance parameters for the VAR parameters α. The third step draws the standard deviation of the volatility innovation. The fourth step draws the stochastic volatilities. The last block draws the unobserved components delivering the estimates for the trend and the cycle.

B.1 VAR Parameters β^T

We condition on the estimated unobserved components for the trend and the cycle $\{\tau_t, C_t\}$, the history of H_t and the stochastic volatility parameters α and draw the non time varying parameters $\{\beta_{q,1}, ..., \beta_{q,pq}\}$ that describe the relationship between the cycle and the auxiliary variables.

The vector of coefficients is sampled from a normal posterior distribution with mean $\overline{M}$ and variance $\overline{\Omega}^{-1}$, based on prior mean M 33 and variance Ω 34 as in Clark (2009). Where $Z_t = \{c_t, AX_{1t}, AX_{2t}\}$ and $X_t = \{c_{t-1}, AX_{1t-1}, AX_{2t-1}, C_{t-2}, AX_{1t-2}, AX_{2t-2}\ 1\}$ for p=2 and k=2.

$$Z_t = BX_t + \upsilon_t, \;\; VAR(\upsilon_t) = \Sigma_t \tag{30}$$

$$\Sigma_t = A^{-1} H_t A^{-1'} \tag{31}$$

$$B \sim (\overline{M}, \overline{\Omega}^{-1}) \tag{32}$$

$$\overline{M} = \overline{\Omega}\{vec(\sum_{t=1}^{T} Q_t^{-1} Y_t X_t') + \Omega^{-1}\}^{-1} \tag{33}$$

$$\overline{\Omega}^{-1} = \Omega^{-1} + \sum_{t=1}^{T} (Q_t^{-1} \bigotimes X_t X_t') \tag{34}$$

B.2 Covariance parameters α

The second block involves the estimation of the covariance parameters for the VAR parameters. In the following, we consider the distribution of α conditional on the data and other parameters. Z^T, X^T and the draw B. This implies knowledge of υ_t . The residuals satisfy the relation described in equation (35). Where ϵ_t is a vector of orthogonalized residuals (structural shocks) with known error variance Λ_t. Λ_t is a diagonal matrix with elements $\lambda_{i,t}$ and $VAR(\epsilon_t) = H_t$. A is a lower triangular matrix with elements αqj, see eq. (36).

As in Cogley and Sargent (2005) the relationship between the residuals and structural shocks will be interpreted as a system of unrelated regressions. The modelling strategy for the law of motion of the variance/covariance matrix is given by the following system of equations: The identity in (38) defines the relation for q=1 . The equations for q=2, 3 can be expressed as transformed regressions with independent standard normals. In this regressions the relation between residuals υ_{it} and structural shocks is transformed proportional to the variance of the structural shocks Λ_t such that $\epsilon^*_{it} \sim N(0,1)$ for i={2, 3}. Therefore, the second equation can be expressed as 39 and the third equation as 40.

$$A\upsilon_t = \epsilon_t \tag{35}$$

$$\begin{bmatrix} 1 & 0 & 0 \\ \alpha_{21} & 1 & 0 \\ \alpha_{31} & \alpha_{32} & 1 \end{bmatrix} \begin{bmatrix} \upsilon_{1,t} \\ \upsilon_{2,t} \\ \upsilon_{3,t} \end{bmatrix} = \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \end{bmatrix}$$

$$A = \begin{bmatrix} 1 & 0 & 0 \\ \alpha_{21} & 1 & 0 \\ \alpha_{31} & \alpha_{32} & 1 \end{bmatrix} \tag{36}$$

$$H_t = \begin{bmatrix} \lambda_{1t} & 0 & 0 \\ 0 & \lambda_{2t} & 0 \\ 0 & 0 & \lambda_{3t} \end{bmatrix} \tag{37}$$

$$v_{1t} = \epsilon_{1t} \tag{38}$$

$$\frac{v_{2t}}{\sqrt{\lambda_{2t}}} = \alpha_{21}(-\frac{v_{1t}}{\sqrt{\lambda_{2t}}}) + \frac{\epsilon_{2t}}{\sqrt{\lambda_{2t}}} \tag{39}$$

$$\frac{v_{3t}}{\sqrt{\lambda_{3t}}} = \alpha_{31}(-\frac{v_{1t}}{\sqrt{\lambda_{3t}}}) + \alpha_{32}(-\frac{v_{2t}}{\sqrt{\lambda_{3t}}}) + \frac{\epsilon_{3t}}{\sqrt{\lambda_{3t}}} \tag{40}$$

B.3 Stochastic Volatilities, Λ^T

The diagonal elements of Λ_t are independent, univariate stochastic volatilities that evolve as geometric random walks without a drift. Based on the draw of A the contemporaneously uncorrelated structural residuals can be computed as specified in (35). The independence MH algorithm can be applied for each orthogonalized VAR residual(ϵ_{it}) conditional on a draw of σ_i.

$$ln\lambda_{it} = ln\lambda_{it-1} + \sigma_i \eta_{it} \tag{41}$$

B.4 Standard deviations of volatility innovations σ_i

Conditional on a draw for λ_{it}, the standard deviations for the volatility innovations σ_i can be drawn from the inverse Gamma distribution42. Assuming an inverse-gamma prior with scale parametersγ_0 and v_0 degrees of freedom, the posterior has an inverse-gamma distribution with degrees of freedom $v_1 = v_0 + T$ and scale parameter $\gamma_1 = \gamma_0 + \sum_{t=1}^{T}(\Delta \ln(\lambda_{it}))$.

$$f(\sigma_i^2 | \lambda_i^T, Y^T) = IG(\frac{v_1}{2}, \frac{\gamma_1}{2}) \tag{42}$$

C Monte Carlo experiment

Figure 11 shows the posterior distribution of the estimated beta parameters. Figure 12 displays the posterior distribution of the covariance parameters resulting from the MC experiment. The real values are marked by the red line and the blue histogram represent distribution of the estimated parameters.

D Additional results

D.1 Trend estimates

Figure 13 displays the median estimated trend of the credit-ratio for the US. Figure 14 displays the median estimated trend of the credit-ratio for the UK

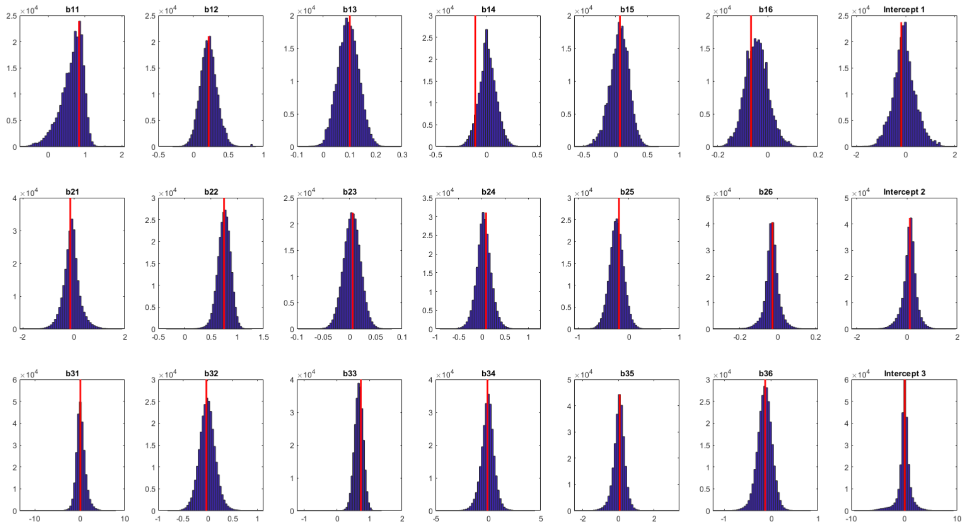

FIGURE 11. Histogram represents the posterior distribution of the estimated beta parameters. Red lines represent the true values.

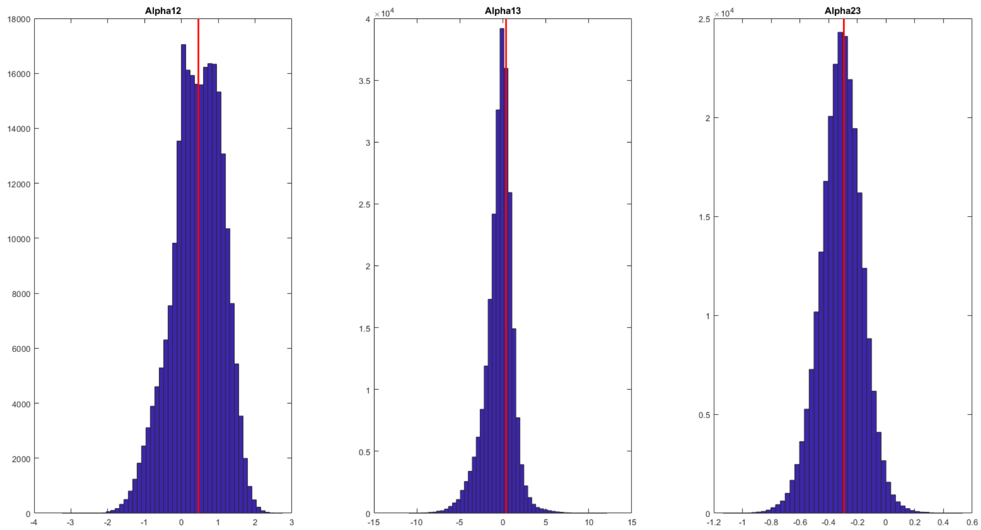

FIGURE 12. Histogram represents the posterior distribution of the estimated covariance parameters. Red line are the true values.

D.2 Stochastic Volatilities

Figure 16 and Figure 17display the estimates for the stochastic volatilities of the latent and observable variables.

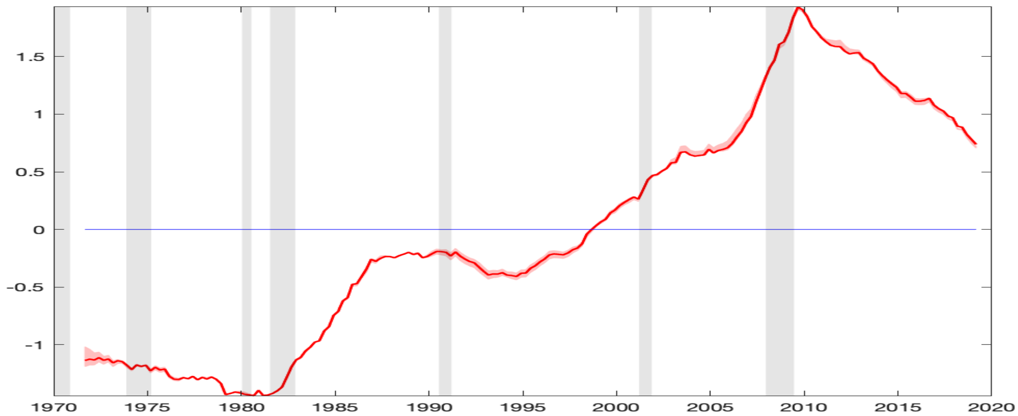

FIGURE 13. Median estimated trend from the decomposition for the US (1971:Q3-2019:Q1), standardized. The shaded area represents the 68% error band. Grey area represents the NBER economic recessions.

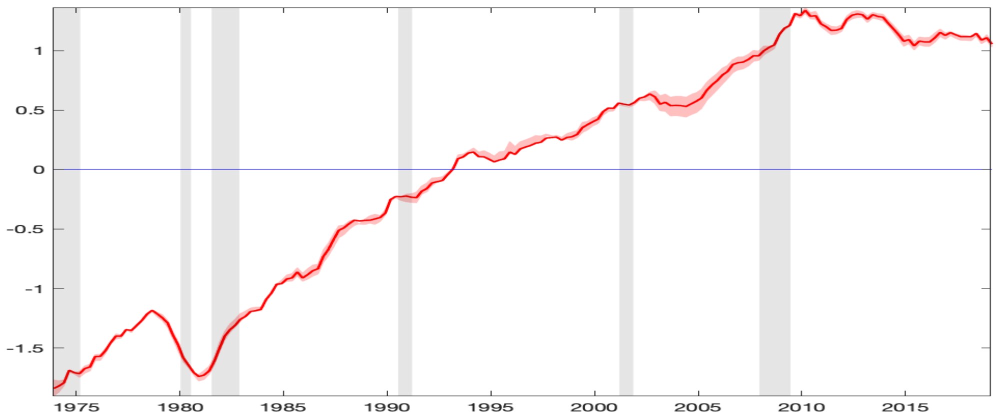

FIGURE 14. Median estimated trend from the decomposition for the U.K (1973:Q4-2019:Q1), standardized. Credit-to-GDP ratio. The shaded area represents the 68% error band. Grey area represents the NBER economic recessions.

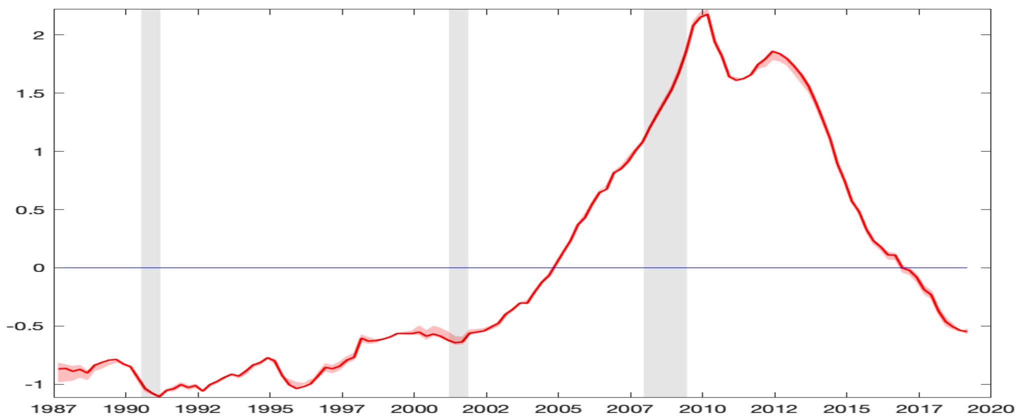

FIGURE 15. Median estimated trend from the decomposition for Ireland (1987:Q3-2019:Q1), standardized. The shaded area represents the 68% error band. Grey area represents the NBER economic recessions.

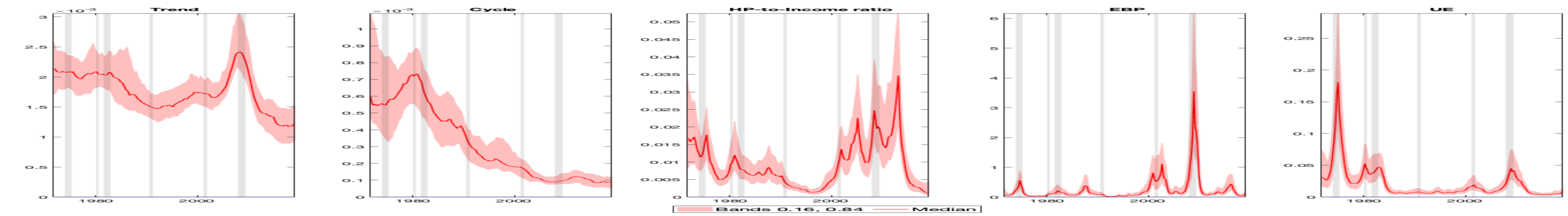

FIGURE 16. Stochastic volatilities. Median estimated stochastic volatilities for the US (1971:Q3-2019:Q1). The shaded area represents the 68% error band. Grey area represents the NBER economic recessions.

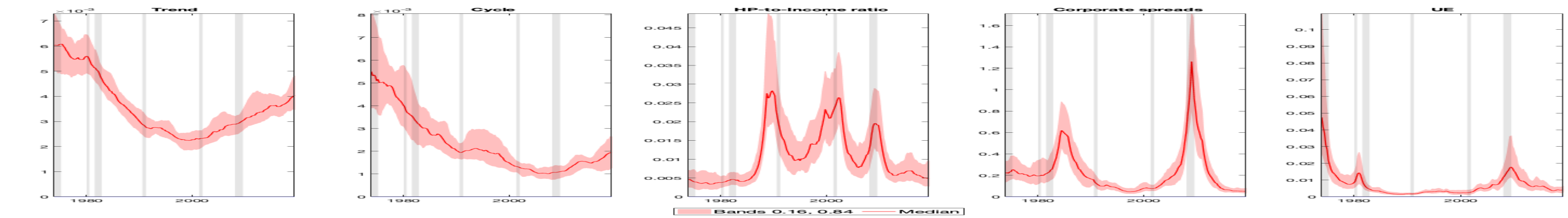

FIGURE 17. Stochastic volatilities. Median estimated stochastic volatilities for the UK (1973:Q3-2019:Q1). The shaded area represents the 68% error band. Grey area represents the NBER economic recessions.

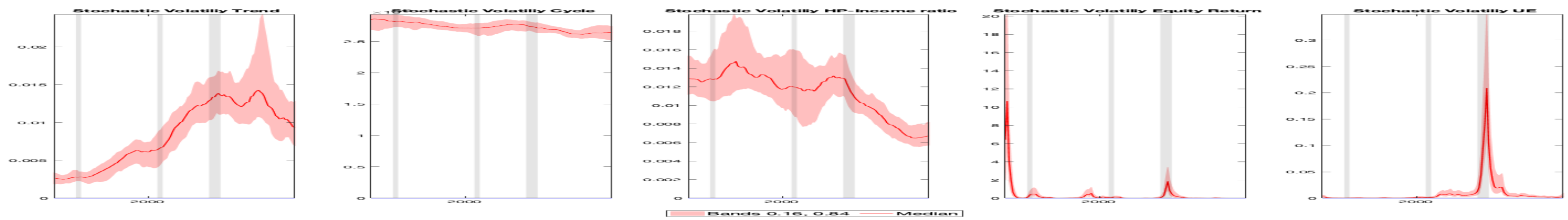

FIGURE 18. Stochastic volatilities. Median estimated stochastic volatilities for Ireland (1987:Q3-2019:Q1). The shaded area represents the 68% error band.Grey area represents the NBER economic recessions.

E Detailed Dataset

TABLE 2. Variables and sources

Country list				
Country	**Target variable**	Auxiliary variable I **Household vulnerabilities**	Auxiliary variable II **Financial conditions / Aggregate risk**	Auxiliary variable III **Economic performance**
	Credit ratio	House-price-to-income-ratio	Excess Bond premium (EBP)	Unemployment
United States	Total credit to the private non-financial sector as % of GDP	Ratio of residential house prices and disposable income, deviations from 10 year averages, rolling basis.	Moody's seasoned BAA corporate relative to Federal Funds Rate (BAAFM)	Deviation from long run average
1961:Q1-2019:Q1	BIS	OECD, FRED, Shiller HP-Index	FRB, FRED	FRED
	Credit ratio	House-price-to-income-ratio	Corporate bond spread	Unemployment
United Kingdom	Total credit to the private non-financial sector as % of GDP	Ratio of residential house prices and disposable income, deviations from 10 year averages, rolling basis.	Spread Corporate bond yield for the UK relative to 10 year government bond yield	Deviation from long run average
1963:Q2-2019:Q1	BIS	OECD, Office for National Statistics (ONS)	BoE, Global Financial data	BoE, ONS
	Credit ratio	House-price-to-income-ratio	Equity return volatility	Unemployment
Ireland	Total credit to the private non-financial sector as % of GNI*	Ratio of residential house prices and disposable income, deviations from 10 year averages, rolling basis.	Log difference of equity index ISEQ return	Deviation from long run average
1977:Q1-2019:Q1	Central Bank of Ireland	OECD	Global Financial data	Global Financial data

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