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Abstract

We apply the multivariate unobserved components model of Rünstler and Vlekke (2018) to jointly estimate the cyclical and trend components of output, credit, and residential property prices in Ireland. We find that credit and house price cycles are subject to an average duration of about 15 years, considerably longer than the business cycle, estimated at 8.5 years. Compared to several alternative estimation methods, the estimates of house price and credit cycles combine strong early warning performance with superior real-time reliability. Our findings contribute to the monitoring of systemic risks in the Irish economy and the conduct of macroprudential policies.

JEL classification: C32, E32, E44, G21, G28

Keywords: Unobserved components models, Vector Error Correction models, Hodrick–Prescott filter, Christiano–Fitzgerald filter, Business cycles, House prices cycles, Credit cycle, Macroprudential policies.

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Non-Technical Summary

Understanding the evolution of credit and housing markets evolve is essential for identifying the buildup of financial vulnerabilities. This research examines the deviation of credit and residential property prices from their long-run equilibrium—commonly referred to as financial cycles—in the Irish economy.

We apply an unobserved components model that separates long-term trends from cyclical movements in the data. By leveraging the interaction between house prices, credit, and the business cycle in Ireland, we estimate the typical duration of each cycle. Our results show that credit and housing cycles in Ireland are significantly longer than the business cycle—around 15 years compared to 8.5 years. This implies that financial booms and busts can build up gradually and persist well beyond regular economic fluctuations.

Consistent with evidence from other EU countries, we find that in Ireland over 1975Q4–2025Q1, changes in house prices tend to occur before shifts in credit and output. This suggests that housing markets may offer early signs of broader financial risks, which could be useful for policy decisions.

We also assess how well these estimated cycles can serve as early warning indicators for systemic crises or stress in the banking sector, particularly when the cycles enter expansionary phases beyond critical thresholds. Our benchmark model performs well in this respect, identifying signals before past episodes of financial distress. Compared to other methods used in policy and research, it shows both higher predictive accuracy and more reliable real-time performance.

This research helps inform macroprudential policy—tools used by authorities to prevent financial instability by offering a clearer, data-driven understanding of Ireland's financial cycles. The results may be particularly relevant for decisions related to the countercyclical capital buffer (CCyB), a key policy instrument designed to build resilience in the banking system during periods of excessive credit growth and wider macro-financial imbalances.

1 Introduction

Estimates of the credit cycle are essential for informing macroprudential policy decisions. The credit cycle should however not be viewed in isolation. The global financial crisis (GFC) has once again highlighted the interplay of boom-bust cycles in credit and residential property markets in precipitating financial instability and crises (Schularick and Taylor, 2012), driven by a mutually reinforcing feedback between mortgage supply and housing prices (Geanakoplos, 2009). Rising property values increase available collateral stimulating mortgage issuance and further elevating prices. Conversely, a drop in property values constrains credit availability. At the same time, leverage cycles interact with fluctuations in economic activity. For instance, major recessions are often preceded by booms in credit and housing markets (Claessens et al., 2011, 2012).[1]

The interactions between credit, housing, and real activity have been especially visible in Ireland. The country has experienced pronounced boom–bust dynamics in credit and housing markets, culminating in a severe banking and economic crisis during the GFC. As a small, open economy deeply integrated into international capital markets, Ireland illustrates the severe impact of global financial shocks in the case of domestic vulnerabilities. In this context, reliable estimates of financial cycles are essential for designing effective macroprudential tools.

In this paper, we apply the multivariate unobserved components model (UCM) proposed in Rünstler and Vlekke (2018) to jointly estimate the trend and cyclical components of GDP, total credit to the private non-financial sector, and residential property prices in Ireland. The central objective is to assess whether this framework can provide a reliable indicator of the Irish financial cycle, which is potentially useful as an early warning indicator of systemic financial crises. We contribute to previous literature on macro-financial cycles in Ireland in two ways. First, we estimate the cyclical fluctuations in the three series jointly within a multivariate framework. Second, we compare the properties of the cycles as early warning indicators for systemic crises against a range of alternative methods, including filters and other multivariate models.

A multivariate time series approach considering the linkages between credit, house price, and business cycles has various advantages over univariate methods. First, unlike univariate filters, it does not rest on prior assumptions about cycle lengths but instead estimates cyclical dynamics. With univariate filters, pre-specified cycle lengths may generate spurious cycles, as discussed, for example, in relation to the Basel III credit-to-GDP gap (Hamilton, 2018; Schüler, 2018). Second, a multivariate framework captures the dynamic interrelations among the series and thereby should provide better insight into the propagation of financial imbalances (Drehmann et al., 2012). Third, by exploiting the information emerging from the cyclical co-movements, multivariate models provide more reliable end-point estimates of cycles, a key feature for informing macroprudential decisions in real time.

Multivariate models employing trend-cycle decompositions have therefore become widely used in practical applications. Key approaches include UCMs (Koopman et al., 2016) and structural vector error correction models (VECMs), where the cycle is derived as the residual of an underlying long-run relationship (Galán and Mencia, 2018). The

[1] For literature on boom-bust cycles in credit and housing and the relations to economic activity see also Mian and Sufi (2010), Jordà et al. (2015, 2016)), and Jordà et al. (2016); Oman (2019), respectively.

specific model used in this paper has been applied by Rünstler et al. (2018) across seventeen EU countries, excluding Ireland. This study applies it specifically to Ireland and evaluates the early warning properties of the estimated cycles. Other studies report that composite indicators may offer better early warning properties than the credit cycle by itself (see Giese et al., 2014 for the UK and Andrea et al., 2017 for Germany).

It is also worth noting that our framework considers GDP and credit as separate variables, rather than relying on the credit-to-GDP ratio as often used in macroprudential analysis. Previous studies have highlighted important limitations of using this ratio, notably the implicit assumption that the long-run income elasticity of credit is equal to one (Juselius and Drehmann, 2015; Buncic and Melecky, 2014). However, this assumption may not hold in economies experiencing financial deepening. Ireland illustrates this case well, having transitioned in recent decades from limited financial access to a more advanced and diversified financial system. Moreover, because business and financial cycles differ in length and amplitude, relying on the credit-to-GDP ratio may obscure important differences in their respective dynamics, potentially distorting early warning signals used for macroprudential policy.

In line with estimates for other advanced economies, our multivariate UCM finds pronounced differences in the duration and timing of Irish macro-financial cycles. The business cycle is estimated to last approximately 8.53 years, while financial cycles — captured through national credit and house prices — extend to 14.75 and 15.35 years, respectively. We also uncover phase shifts across cycles: turning points in house prices are found to lead those in credit by nearly two years, while GNI leads credit by about half a year. These results suggest a transmission mechanism in which shocks first manifest in house prices, and subsequently propagate to real activity and credit growth.

We then proceed with evaluating the early warning performance of the cycles obtained from the UCM against a range of alternative models. Our analysis leverages crisis databases from Laeven and Valencia (2020), Babecky et al. (2014), and Baron and Dieckelmann (2021), from which we select episodes of systemic crises. In addition, we include episodes of banking distress, defined as substantial contractions in the domestic assets of domestic credit institutions. We construct optimal thresholds on for the levels of credit and house price cycles based on their predictive performance in identifying systemic crisis to help inform macroprudential policy decisions.

We find that the national credit and house price cycles estimated with our benchmark model exhibit strong early-warning properties for systemic crises in Ireland, outperforming alternative approaches. The Christiano–Fitzgerald filter applied to the national credit series (Christiano and Fitzgerald, 2003) likewise displays robust early-warning performance. However, the reliability of real-time from the filter fall short of those produced by the benchmark estimates. Two alternative multivariate time series models due to Galán and Mencia, 2018 and O'Brien and Velasco (2020) show clearly less satisfactory early warning properties.

The remainder of this paper is structured as follows. Section 2 reviews the literature on financial cycle estimation as well as the literature on Ireland's economic and financial cycles. Section 3 describes the multivariate UCM and alternative models. Section 4 presents the estimated cycles and relates their turning points to historical developments. Section 5 evaluates the early warning and real time properties of the estimated cycles. Additional figures and tables are provided in Appendix 7.

2 Literature Review

2.1 Empirical literature on financial cycles

The estimation of credit and housing cycles remains a critical yet challenging area within macroprudential policy research. A diverse set of methodologies has emerged for this purpose, ranging from turning point analysis (Claessens et al., 2012), univariate filters (Aikman et al., 2015; Drehmann et al., 2012) and spectral methods (Schüler et al., 2015, 2020; Scharnagl and Mandler, 2019a) to multivariate frameworks based on UCMs (Koopman et al., 2016; Rünstler and Vlekke, 2018; O'Brien and Velasco, 2020) or vector autoregressions (Galán and Mencia, 2018; Lang and Welz, 2018).

Early empirical studies primarily rely on univariate filtering methods, such as the Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1997) and the Christiano-Fitzgerald band-pass filter (Christiano and Fitzgerald, 2003). While the application of these filters is straightforward, it has drawn criticism for the arbitrary specification of the filter bandwidths and the high sensitivity of the estimates to end-point bias (Hamilton, 2018; Schüler, 2018). Drehmann et al. (2012) propose filter bandwidths of 32 to 120 quarters for the extraction of credit and house prices cycles, which compares to bandwidths of 8 to 32 quarters used for business cycles. While this choice accounts for the longer duration of financial cycles, the use of pre-defined filter bands may distort the estimates in various ways. For instance, the distinct bandwidths for business and financial cycles enforce a potentially artificial divergence between the respective estimates.

The limitations of pre-defined filter bands can be overcome by means of spectral methods to estimate the frequency bands characterizing credit and house price cycles. Schüler et al. (2020) employ "power cohesion" to extract common cyclical fluctuations in credit and asset prices and to derive the frequency bands from cross spectral densities. However, their approach ignores information in the auto spectra. Mandler and Scharnagl (2022) and Scharnagl and Mandler (2019b) use wavelet analysis to study the co-movement of financial cycles within and across euro area economies.

These studies share the insight that credit and house prices are typically subject to medium-term cycles with a longer duration compared to traditional business cycles. The two cycles are in general subject to close co-movement, reflecting the feedback mechanism via the value of collateral depicted by Geanakoplos (2009). GDP also participates in medium-term fluctuations beyond the traditional business cycle. Furthermore, across countries, the co-movement of credit and house prices is weaker than that observed for business cycles.

Univariate filters and spectral methods do not explicitly model the interdependencies among the macro-financial variables. Studies have used multivariate approaches to incorporate this information in the estimation process, thereby enhancing both the theoretical coherence and the predictive accuracy of credit cycle measures.

Most multivariate approaches employ an unobserved components framework. Koopman et al. (2016) estimate a standard multivariate structural time series model (STSM) for GDP, credit volumes, and housing prices, extended with the ratios of credit to GDP and to disposable income. The approach assumes that the series participate at both a business and a financial cycle with certain phase shifts. Rünstler and Vlekke (2018) extend on the specification by allowing for richer cyclical dynamics. Lang and Welz (2018) and Galán and Mencía (2021) propose semi-structural UCMs to obtain estimates of credit gaps, defined as deviations of the credit-to-GDP ratio from its long-run trend. In these models, the trend is estimated from a multivariate specification, while the cycle is modeled as an autoregressive process. As an alternative to UCMs, vector error correction models (VECMs) have also been applied, such as in Galán and Mencia (2018), who estimate the credit-to-GDP ratio using real house prices, GDP, and interest rates as endogenous variables.

As to Ireland, O'Brien and Velasco (2020) estimate the national credit cycle using an extension of the univariate UCM of Harvey (1985) by employing auxiliary variables to enhance the identification of the cyclical component. The credit trend component is estimated in an univariate setup, while a vector autoregressive (VAR) structure is used to estimate the cyclical component. Further, the model introduces stochastic volatility in both trend and cyclical innovations. The application of the model to the Irish case considers house price-to-income ratio, equity volatility, and unemployment to estimate the cyclical component of the credit cycle.

Among studies estimating Irish housing cycles, Egan and McQuinn (2023) use a Markov switching model to analyze housing market dynamics in the post-pandemic period in Ireland and find that house price inflation remained above its estimated long-term fundamentals until the end of 2023. Yao (2022) apply a UCM augmented with auxiliary variables to identify both trend and cyclical components of the house-price-to-income ratio, revealing that the series stood above its long-run equilibrium at that time. Furthermore, McQuinn et al. (2024) evaluate Irish house price developments against long-term fundamentals.

2.2 An overview of Irish economic and financial cycles

A number of studies have examined the evolution of Ireland's economic and financial cycles, documenting the various phases of contraction and expansion, which were in many instances closely aligned with global economic fluctuations. This section presents a selective overview aimed at highlighting the major turning points in the cycles to inform the subsequent discussion of our estimates.

Starting with the 1970s, in the second half of the decade there was an extraordinary influx of foreign firms, with mostly U.S. high-tech and pharmaceutical companies establishing significant production facilities in Ireland, which contributed to a period of economic expansion (Ahearne et al., 2006).

The expansion reversed in the early 1980s, when the Irish economy turned into a lasting recession along with the international environment prompted by the earlier fiscal and monetary policy expansion (Geary, 1992; FitzGerald, 2019). The contraction triggered a currency crisis, which began in 1985Q3 and kept the exchange rate under persistent depreciation pressures until 1988Q2 (Babecky et al., 2014). The recession lasted until the mid-1990s, interrupted only by a short-lived recovery between 1987 and 1989. The recovery was also characterized by a sharp fiscal consolidation and triggered some debate about whether a Ricardian equivalence mechanism supported consumption through the anticipation of lower future taxes (FitzGerald, 2019).

For the period thereafter, the literature highlights the unfolding of the *Celtic Tiger* period in the second half of the 1990s, associated with strong growth underpinned by renewed inflows of foreign direct investment (O'Sullivan and Kennedy, 2010; Ahearne et al., 2006). However, scholars also stress the emergence of an asset price bubble in the late 1990s and early 2000s, particularly in the real estate sector. Drawing on assessments from the IMF and other institutional sources, Baudino et al. (2020)

argue that, although economic growth was robust during the 1990s, its fundamentals weakened in the early 2000s, becoming increasingly reliant on domestic demand.

This dynamics was reinforced by the creation of the euro area in 1999, as the boost to financial integration facilitated access to foreign credit, which in turn fostered property-led growth (Clarke and Hardiman, 2012, Baudino et al., 2020). Importantly, Lane (2011) characterizes the adoption of the euro as an asymmetric shock, as the integration into a deeper euro capital market affected peripheral economies like Ireland to a particular extent by significantly lowering external funding premia. Altogether these developments enhanced the availability of credit, which in turn led Irish banks to accumulate increasing exposures to the real estate sector. Rising real estate values, in turn, increased household wealth, fueling consumption and the economic expansion.

This prolonged boom led to a build-up of significant vulnerabilities within the banking sector, particularly through concentrated exposures to property-related lending. The GFC therefore had a massive impact on Irish banks. Funding pressures peaked in late 2008 and again in 2010 Baudino et al. (2020). From late 2011 onwards, and supported by economic recovery programmes, banks gradually regained access to deposits and unsecured bond markets, facilitating the restoration of credit supply. Despite some signs of easing in the contraction of credit, private lending remained on a pronounced downward trajectory until late 2013. This pattern is consistent with country reports, which document that both the fall in credit began to moderate and the property market started to recover from 2013 onwards, coinciding with the conclusion of the EU/IMF Programme in December 2013 (Baudino et al., 2020).

Turning to more recent developments, several reports highlight the impact of large-scale fiscal and monetary support measures adopted in response to the COVID-19 crisis. Loan guarantees, credit moratoria, and liquidity facilities implemented across the EU are argued to have stabilized credit supply and supported its subsequent recovery (Central Bank of Ireland, 2021; European Systemic Risk Board, 2020).

As to the most recent estimates, Irish house prices have remained above their long-run trend during the post-pandemic period until 2024 (Egan and McQuinn, 2023, McQuinn et al., 2024), reinforcing the view that current housing price inflation reflects sustained demand coupled with supply constraints. Similarly, using a UCM, Yao (2022) finds the house-price-to-income ratio in Ireland to be above trend in 2021. Similarly, the Central Bank of Ireland's output gap assessments — drawing on a combination of univariate filters, multivariate models, and production function approaches— indicate that economic activity remained above potential in late 2024, although they point to a moderation of the economic expansion (Central Bank of Ireland, 2024).

The literature further shows that Ireland's economic and financial cycles have often overlapped with episodes of systemic crisis and banking distress. Laeven and Valencia (2020) identify systemic banking crises associated with the global financial crisis and the subsequent sovereign debt crisis, between 2008Q1 and 2010Q2 and 2010Q3 and 2012Q4, respectively. Using a range of international crisis datasets, Babecky et al. (2014) date a currency crisis in 1985Q1, however, Baudino et al. (2020) argue that the crisis persisted for a number of quarters. Finally, Baron and Dieckelmann (2021) highlight large bank equity declines in 1974, 1990, and 2016, though these episodes are not generally classified as systemic crises in the Irish case, as there is little evidence of banking panics.

3 Methodology

We apply the multivariate structural time series model (STSM) proposed by Rünstler and Vlekke (2018). The basic multivariate STSM due to Harvey and Koopman (1997) is designed to decompose a set of non-stationary series into trend, cycle, and irregular components using the stochastic cycle (SC) as the building block for modelling cyclical dynamics. Rünstler and Vlekke (2018) extend the model by enhancing the specification of cyclical dynamics to account for the higher persistence of financial cycles and for phase shifts of the latter against the business cycle (Rünstler, 2004).

The section is structured as follows. Subsection 3.1 introduces the benchmark model of Rünstler and Vlekke (2018). Subsection 3.2 outlines the estimation strategy. Subsection 3.3 presents alternative univariate and multivariate methods for estimating financial cycles.

3.1 Trend and cyclical dynamics

The model decomposes each observed variable into a stochastic trend, a cyclical component, and an irregular term:

$$\mathbf{x}_t = \boldsymbol{\mu}_t + \mathbf{x}_t^C + \boldsymbol{\varepsilon}_t \ . \tag{1}$$

The $n \times 1$ vector $\boldsymbol{\varepsilon}_t$ of irregular components is normally and independently distributed with mean zero and $n \times n$ covariance matrix Σ_ε, $\boldsymbol{\varepsilon}_t \sim \mathrm{NID}(\mathbf{0}, \Sigma_\varepsilon)$. The $n \times 1$ vector $\boldsymbol{\mu}_t$ of stochastic trend components follows a random walk with a time-varying slope $\boldsymbol{\beta}_t$, which is again specified as a random walk.

$$\begin{aligned} \boldsymbol{\mu}_t &= \boldsymbol{\mu}_{t-1} + \boldsymbol{\beta}_{t-1} + \boldsymbol{\eta}_t, & \boldsymbol{\eta}_t &\sim \mathrm{NID}(\mathbf{0}, \Sigma_\eta) \ , \\ \boldsymbol{\beta}_t &= \boldsymbol{\beta}_{t-1} + \boldsymbol{\zeta}_t, & \boldsymbol{\zeta}_t &\sim \mathrm{NID}(\mathbf{0}, \Sigma_\zeta) \ , \end{aligned} \tag{2}$$

The level $\boldsymbol{\eta}_t' = (\eta_{1,t}, ..., \eta_{n,t})'$ and slope innovations $\boldsymbol{\zeta}_t' = (\zeta_{1,t}, ..., \zeta_{n,t})'$ are normally and independently distributed with $n \times n$ positive semi-definite covariance matrices Σ_η and Σ_ζ, respectively. Specification (2) amounts to a multivariate local linear trend as introduced by Harvey and Koopman (1997).

Cyclical components $\mathbf{x}_t^C = (x_{1,t}^C, ..., x_{n,t}^C)'$ are specified as linear combinations of n independent stochastic cycles $\widetilde{\psi}_{i,t} = (\psi_{i,t}, \psi_{i,t}^*)'$, $i = 1, \dots, n$. We first review the extended stochastic cycle (SC) and then describe the specification of $\mathbf{x}_t^C$. The extended SC $\widetilde{\psi}_{i,t}$ is defined as the *bivariate* stationary first-order autoregressive process

$$(1 - \phi_i L) \left(I_2 - \rho_i \begin{bmatrix} \cos \lambda_i & \sin \lambda_i \\ -\sin \lambda_i & \cos \lambda_i \end{bmatrix} L \right) \begin{bmatrix} \psi_{i,t} \\ \psi_{i,t}^* \end{bmatrix} = \begin{bmatrix} \kappa_{i,t} \\ \kappa_{i,t}^* \end{bmatrix} . \tag{3}$$

with decays $0 < \rho_i < 1, 0 < \phi_i < 1$ and frequency $0 < \lambda_i < \pi$. I_2 denotes the 2×2 identity matrix, while *L* is the lag operator. We assume that cyclical innovations $\widetilde{\kappa}_{i,t} = (\kappa_{i,t}, \kappa_{i,t}^*)'$ are standardised to $\widetilde{\kappa}_{i,t} \sim \mathrm{NID}(\mathbf{0}, I_2)$. For $\phi_i = 0$ the model reduces to the standard specification of Harvey and Koopman (1997).The standard SC is restricted to have a complex conjugate root.

Rünstler and Vlekke (2018) introduce the additional autoregressive term $(1 - \phi_i L)$ to accommodate the high persistence of financial cycles. The autocovariance generating function (ACF) $\widetilde{V}_{ii}(s) = \mathbb{E}\left[\widetilde{\psi}_{i,t}\widetilde{\psi}'_{i,t-s}\right]$ for $s = 0, 1, 2, \ldots,$ is therefore given by dampened cosine and sine waves of period $2\pi/\lambda_i$,

$$\widetilde{V}_{ii}(s) = h(s;\rho_i,\phi_i)T^{+}(s\lambda_i); \tag{4}$$

$$T^{+}(s\lambda_i) = \begin{bmatrix} \cos(s\lambda_i) & \sin(s\lambda_i) \\ -\sin(s\lambda_i) & \cos(s\lambda_i) \end{bmatrix},$$

with scalar function $h(s;\rho_i,\phi_i) = (1-\rho_i^2)^{-1}(1-\phi_i^2)^{-1}\rho_i^s\phi_i^s$. Note that $\psi_{i,t}$ and $\psi^*_{i,t}$ share similar dynamics, while matrix $T^{+}(s\lambda_i)$ is skew-symmetric.

We turn to the specification of cyclical components $\mathbf{x}_t^C$. In case of a univariate STSM, the cycle is simply defined as $x^C_{1,t} = a_1\psi_{1,t}$ with scaling factor a_1, while $\psi^*_{1,t}$ serves as an auxiliary variable. For the multivariate case, we assume that vector $\mathbf{x}_t^C$ is driven by n independent latent stochastic cycles. Specifying the elements of $\mathbf{x}_t^C$ as linear combinations of both $\psi_{i,t}$ and $\psi^*_{i,t}$ allows for modeling cyclical co-movements among the n series in terms of phase-adjusted covariances and phase shifts (Rünstler, 2004).

For this purpose, define the $n \times 1$ vectors $\boldsymbol{\psi}_t = (\psi_{1,t}, \ldots, \psi_{n,t})'$ and $\boldsymbol{\psi}^*_t = (\psi^*_{1,t}, \ldots, \psi^*_{n,t})'$. The $n \times 1$ vectors of innovations $\boldsymbol{\kappa}_t$ and $\boldsymbol{\kappa}^*_t$ are defined equivalently. They are assumed to be altogether uncorrelated, $\mathbb{E}\left[\boldsymbol{\kappa}_t\boldsymbol{\kappa}_t'\right] = \mathbb{E}\left[\boldsymbol{\kappa}^*_t\boldsymbol{\kappa}^{*\prime}_t\right] = I_n$ and $\mathbb{E}\left[\boldsymbol{\kappa}_t\boldsymbol{\kappa}^{*\prime}_t\right] = 0$.

Cyclical components $\mathbf{x}_t^C$ are then specified as

$$\mathbf{x}_t^C = A\boldsymbol{\psi}_t + A^*\boldsymbol{\psi}^*_t\ , \tag{5}$$

where $A = (a_{ij})$ and $A^* = (a^*_{ij})$ are general $n \times n$ matrices. Given the emphasis of studies on the different dynamics of business and housing cycles, Rünstler and Vlekke (2018) abandon the assumption that all SCs share similar dynamics, i.e. the restriction $\phi_i = \phi$, $\rho_i = \rho$, $\lambda_i = \lambda$ for $i = 1, \ldots, n$.

From equation (5), cyclical components $\mathbf{x}_t^C$ may load, via matrices A and A^*, on n latent independent SCs with potentially different dynamics. The specification therefore provides a flexible approach to modeling cyclical co-movement. At the same time, the symmetry properties of the SC allow for an interpretation of cyclical dynamics in terms of cycle length and decay, together with pairwise coherence and phase shifts across components. Coherence is a measure between 0 and 1 that expresses the degree of co-movement between two cycles, abstracting from their lead-lag relationships (phase shifts). As the analytical expressions provided by Rünstler (2004) no longer apply once the assumption of similar dynamics is relaxed, Rünstler and Vlekke (2018) derive these statistics numerically from the joint spectral density function of the estimated cycles.

3.2 Estimation

The model consists of equations (1), (2), and (5) with the elements $\widetilde{\psi}_{i,t} = \left(\psi_{i,t}, \psi^*_{i,t}\right)$ of vectors $\boldsymbol{\psi}_t = (\psi_{1,t}, \ldots, \psi_{n,t})'$ and $\boldsymbol{\psi}^*_t = (\psi^*_{1,t}, \ldots, \psi^*_{n,t})'$ following stochastic processes as defined in equation (3). The model parameters are given by the elements of matrices Σ_η, Σ_ζ, A, and A^* together with ϕ_i, ρ_i, and λ_i, $i = 1, \ldots, n$. Innovations $\boldsymbol{\varepsilon}_t$, $\boldsymbol{\eta}_t$, $\boldsymbol{\zeta}_t$, $\boldsymbol{\kappa}_t$, and $\boldsymbol{\kappa}^*_t$ are assumed to be mutually uncorrelated.

We estimate the model from Bayesian methods by casting it in state-space form

$$\mathbf{x}_t = Z\boldsymbol{\alpha}_t + \boldsymbol{\varepsilon}_t,$$
$$\boldsymbol{\alpha}_{t+1} = W\boldsymbol{\alpha}_t + \xi_t$$

and applying the prediction error decomposition of the Kalman filter. The state space form is detailed in Supplement A in Rünstler and Vlekke (2018). We use the routines provided by `Dynare`, a MATLAB-based platform for economic modeling, which implement the Gibbs sampler due to Carter and Kohn (1994) for the state simulation step. Our prior distributions for the structural parameters, including the elements of variance-covariance matrices and the parameters guiding cyclical dynamics, are taken from Rünstler et al. (2018).[2]

3.3 Alternative Models

In this subsection, we present a set of alternative models that serve as points of comparison for our benchmark estimates. These alternatives are used to evaluate both the early-warning and the real-time properties of our cyclical estimates.

Among the series estimated with the benchmark model, we include the credit cycle, the house price cycle, and a financial cycle indicator constructed as the average of the standardized credit and house price cycles. This construction ensures equal weight to both series and serves as a useful benchmark for comparison. The approach follows the empirical literature Giese et al., 2014; Andrea et al., 2017 and the recommendations of the ESRB ESRB (2014), which suggest that composite indicators may in some cases provide superior early-warning signals relative to individual series.

Among the univariate methods, we first employ the Hodrick–Prescott (HP) filter, as recommended by the European Systemic Risk Board (ESRB) for estimating the credit-to-GDP gap (see ESRB, 2014). In line with this guidance, many EU countries adopt the filter with a high smoothing parameter of 400,000 to capture long-term trends in credit developments. Second, we use the Christiano–Fitzgerald (CF) band-pass filter. For business cycles, Baxter and King (1999) have recommended a frequency band of 8-32 quarters, while for credit cycles Aikman et al. (2015) use a band of 32-120 quarters. The filters are applied in a one-sided, recursive manner on an expanding sample, starting with an initial 40-quarter period, (see also Hamilton, 2018).

Regarding alternative multivariate models, we first estimate a Vector Error Correction (VEC) model, following the empirical strategy proposed by Galán and Mencia (2018). This framework allows for the identification of long-run equilibrium relationships among non-stationary macro-financial variables by exploiting co-integration. The set of endogenous variables, proposed by the authors, includes national credit (c_t), GDP (y_t), loan interest rates (r_t), and house prices (hp_t). In the Irish case, we employ GNI (y_t) and real interest rates of loans to households. All variables are expressed in real terms, deflated using the Consumer Price Index (all items) (see Table A.2).

The model captures short-term dynamics through a Vector Autoregressive (VAR) structure in first differences, with long-run relationships represented as co-integrating vectors as follows:

$$\begin{aligned} \Delta Y_t &= \gamma + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \alpha \tilde{\mu}_{t-1} + \varepsilon_t; \\ \tilde{\mu}_{t-1} &= \mu + \beta Y_{t-1}, \end{aligned} \tag{6}$$

[2]The DYNARE code is a version of the one developed by Dmitry Kulikov in the context of Rünstler et al. (2018).

where Δ denotes the first difference operator, $Y = (c_t, y_t, r_t, hp_t)$ is a vector of endogenous variables of adjustment coefficients, α is a matrix of adjustment coefficients of long-run deviations containing one vector for each of the variables, analogously, β' contains the four co-integrating vectors, Γ_i represents p-1 matrices of parameters of lagged underlying variables, where p is the lag order of the VAR in levels, μ is a vector of intercepts, and ε_t is the error term.

The long-run relationship is represented by the error correction term ($\tilde{\mu_t}$). Following Galán and Mencia (2018), the credit cycle c^c is given by the deviation of credit from long-run equilibrium:

$$c_t^c = c_t - \mu - \beta_y \cdot y_t - \beta_r \cdot r_t + \beta_{hp} \cdot hp_t, \tag{7}$$

where r_t denotes the long-term real interest rate, hp_t the real house price index, and β_r, β_{hp} are the corresponding coefficients.

Galán and Mencia (2018), given their objective of estimating the trend and cycle of the credit-to-GDP ratio, impose a unit long-run elasticity of credit to GDP in equation (7) by setting $\beta_y = 1$. However, we prefer to estimate elasticity β_y.

When estimating the model with the four variables proposed by Galán and Mencia (2018) for Ireland, we identify two cointegrating relationships. A more parsimonious version using only credit, GDP, and house prices yields a single cointegrating vector. We refer to these specifications as VEC_GM2 and VEC_GM1, respectively, where VEC_GM1 denotes our customized version of the model. Figure A.14 shows the estimated cointegration relationship comparing the data with the error correction term and the estimated national credit cycle. In our assessment of early-warning properties, we report only the best-performing specification among these two for parsimony.

Finally, we consider the model proposed by O'Brien and Velasco (2020), which decomposes the target variable into a stochastic trend and a cyclical component using an unobserved components framework.[3] The authors introduce stochastic volatility in both trend and cyclical innovations, a feature which renders the filter highly non-linear. The cyclical component is modeled jointly with auxiliary variables through a Bayesian VAR (BVAR), including the house price-to-income ratio, the unemployment rate, the return on equity, and the return on equity volatility of the Irish Stock Exchange (ISEQ). The cycle is extracted from national credit-to-GNI.

[3]At the Central Bank of Ireland, credit cycle estimates based on this model have been updated using an in-house adaptation for implementation purposes. This paper relies on that adaptation.

4 Empirical Results

After a description of the data in Subsection 4.1, we present the estimates of trends and cycles in GNI, national credit, and house prices in Subsection 4.2 and discuss their properties. Subsection 4.3 then discusses the estimated turning points of these cycles against the previous literature reviewed in Subsection 2.2.

4.1 Data

We use three series: an indicator of real economic activity, the total volume of credit to the private sector, and an index of real residential property prices.

We employ Modified Gross National Income (GNI*) —for simplicity, GNI hereafter, as a more accurate reflection of Ireland's domestic economic conditions. This choice is motivated by structural features of the Irish economy. In particular, the large presence of multinational corporations distorts GDP through profit shifting and intellectual property transfer (O'Grady, 2024). Notably, the credit extended to households and domestic non-financial corporations in Ireland, is more directly linked to GNI than to GDP.

Table A.1 in Appendix 7 reports the variables used along with their data sources and identifiers for reproducibility. The GNI data, originally available on an annual basis from the Central Statistics Office (CSO), are interpolated to quarterly frequency using the Chow-Lin method (Chow and Lin, 1971), with unemployment and Modified Domestic Demand (MDD) series serving as auxiliary variables. Real house prices are based on the Residential Property Price Index (RPP), reported by the CSO and covering all residential property types nationwide. Credit data combine outstanding loans to households (sourced from the ECB) and outstanding credit to non-financial corporations provided by domestic financial institutions (sourced from the Central Bank of Ireland). This variable is labeled as National Credit (NC).

The sample period ranges from 1975Q4 to 2025Q1.[4] Monthly indicators are converted to quarterly frequency by taking the within-quarter average. Nominal variables are deflated using the Consumer Price Index (all items), expressed in 2025Q1 prices. Finally, all series are taken in logarithms and seasonally adjusted using the ARIMA-based X13 method.[5] Table A.2 in Appendix 7 presents the descriptive statistics of the data employed in the estimation model.

4.2 Main estimates

Figures 1, 2, and 3 display the estimated trend and cyclical components for the national credit, house prices, and GNI, respectively, whereas Table 1 summarizes the main characteristics of the estimated cycles.

The estimated average length of credit and house price cycles is approximately 15 years: 14.75 years for credit and 15.35 years for house prices. The business cycle, proxied by GNI, is notably shorter (8.53 years). The sizes of the cycles differ markedly

[4] Some historical series are not publicly available and were provided by the Central Bank of Ireland. These include quarterly GNI (pre-1998Q1), national credit (pre-2002Q4) and residential property prices (pre-2004Q4), and monthly household loan rates (pre-2003M2) and domestic total assets (pre-2003M1).

[5] Implemented via the `x13()` function from the `RJDemetra` R package.

as well: a standard deviations of 1.9 % for GNI compares to values of 4.1 % and 10.6 % for credit and house prices, respectively.

As for cyclical co-movements, the coherence between GNI and credit is fairly high at 0.91 (see Table 1). The coherences of house price cycles with GNI and credit cycles turn out somewhat lower taking values of 0.64 and 0.42, respectively. Partly, these lower values arise from the fact that GNI and credit also display a fairly close co-movement at the shorter business cycle frequencies, at which house prices hardly participate.[6]

The estimated phase shifts offer insights into the temporal structure of macro-financial fluctuations in the Irish economy. Figure 4 displays the estimated financial cycles together, from which we can observe that house price cycles (HP) precede credit cycles (NC). Accordingly, house price cycles are found to lead those in national credit with a phase of $\theta_{(RPP,NC)} = 2.37$ years (see Table 1). Even though the business cycle exhibits a shorter duration, house prices also lead GNI by $\theta_{(RPP,GNI)} = 0.90$ years, while GNI leads national credit by $\theta_{(GNI,NC)} = 0.54$ years. These results suggest a transmission mechanism in which shocks first manifest in house prices, subsequently propagate to real activity, and eventually impact credit growth, highlighting differentiated timing in macro-financial responses to common shocks.

TABLE 1. Cyclical Properties – Benchmark UCM

	GNI	National Credit	House Prices
Cycle Length (Years)	8.534	14.748	15.347
Std. Deviation (x 100)	3.441	6.915	9.984
Coherence	GNI	National Credit	House Prices
GNI	–	0.912	0.638
National Credit	–	–	0.421
House Prices	–	–	–
Phase Shift (Years)	GNI	National Credit	House Prices
GNI	–	−0.540	0.902
National Credit	–	–	2.370
House Prices	–	–	–

Note: Coherence measures the degree of co-movement (0 to 1) between two cycles, abstracting from phase shifts. A negative phase shift means the row variable leads the column variable.

[6]The weaker co-movement between housing and credit cycles in Ireland is in line with estimates for other countries found by Rünstler et al. (2018), such as values of 0.44 and 0.60 for Spain and the UK, respectively.

FIGURE 1. Benchmark Results - GNI

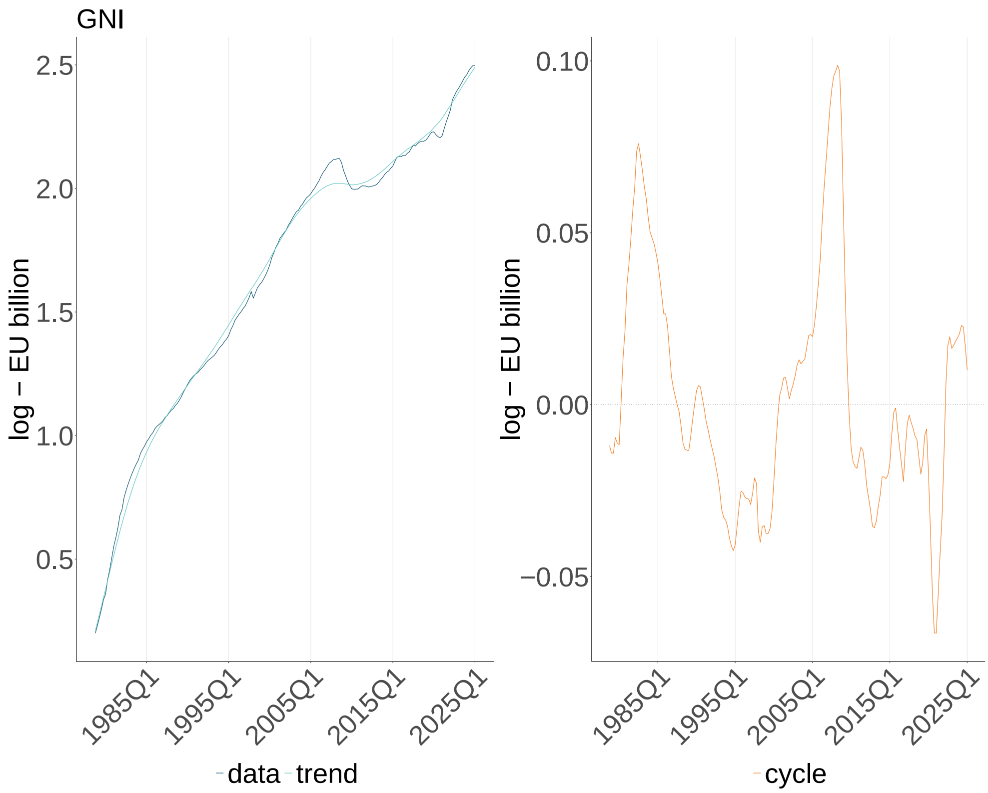


FIGURE 2. Benchmark Results - National Credit

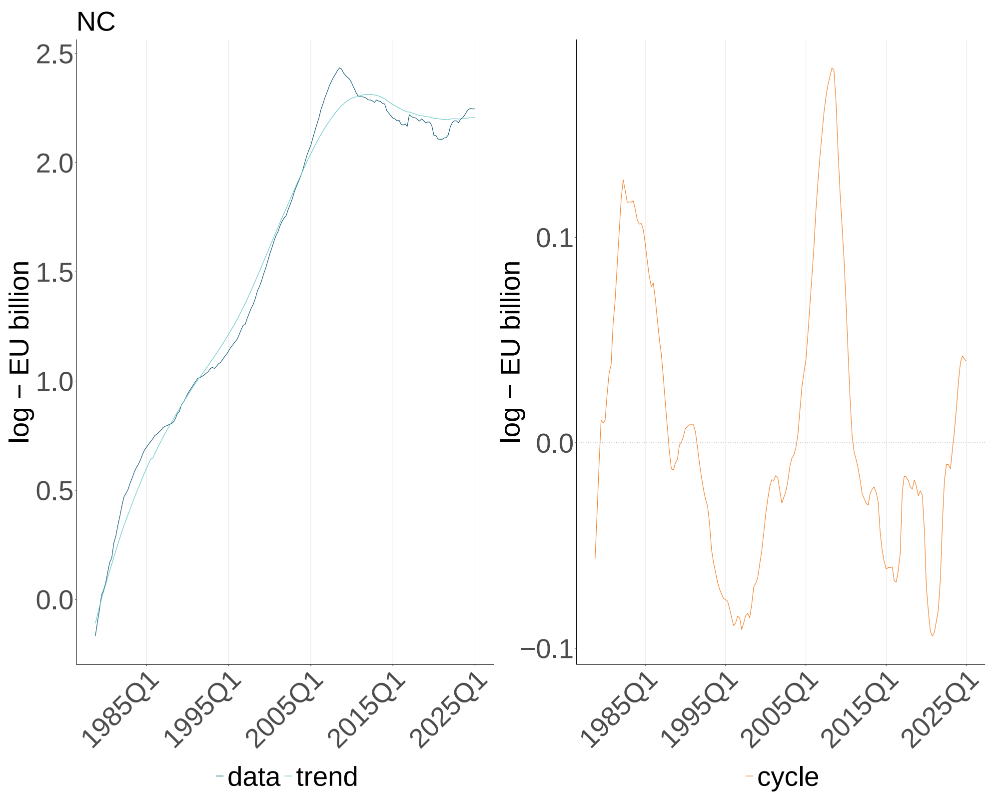


FIGURE 3. Benchmark Results - House Prices

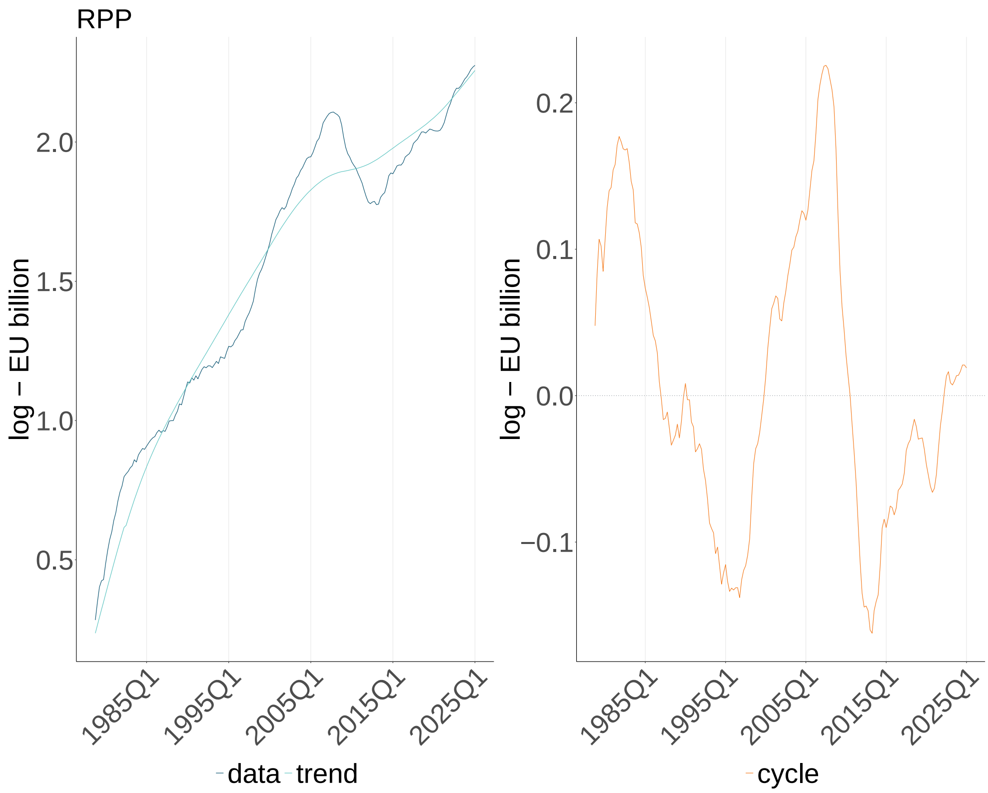
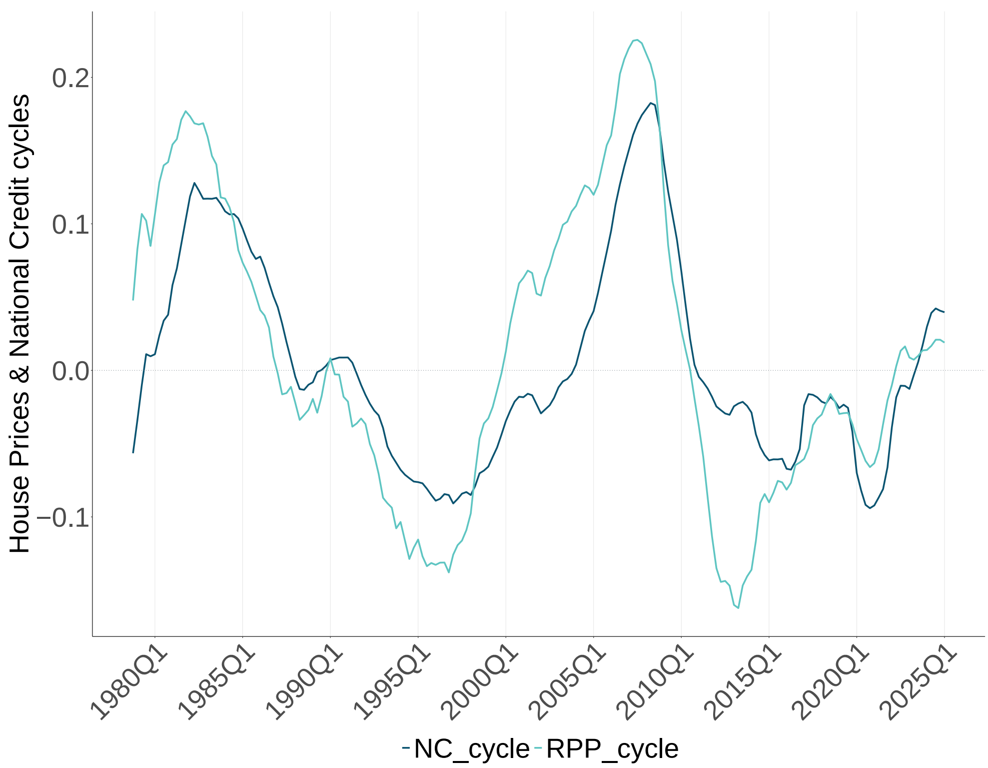


FIGURE 4. Benchmark Results - House Price and National Credit Cycles



These outcomes are broadly consistent with other countries in the euro area, as reported e.g. by Rünstler et al. (2018), who applied the model across a set of EU member states. As shown in Table A.3 in the appendix, the length of the Irish financial cycle is similar to that of the UK and the EU17 average.[7] Moreover, the standard deviations of the estimated business and credit cycles in Ireland fall within the euro area 25th–75th percentiles, whereas the standard deviation of the house price cycle is somewhat higher than the corresponding euro area range.

4.3 Main turning points in the estimated cycles

The turning points identified in our three estimated cycles are largely consistent with the evidence documented in the literature on Irish economic history discussed in Section 2.2.

Our estimates indicate that the business cycle was in an expansionary phase until 1982Q4, when the economy turned into a recession. The trough was reached in 1994Q4. For the period of 1989Q2 to 1990Q4 our estimate show a short-lived expansionary phase, possibly driven by deflationary policies that temporarily boosted consumption (FitzGerald, 2019). The Celtic Tiger era is documented as beginning in the second half of the 1990s (O'Sullivan and Kennedy, 2010; FitzGerald, 2019). Our estimates indicate that the cyclical trough was reached in 1995Q3. In 1999Q the cycle turned positive, a state that persisted until the onset of the GFC. After the GFC, the cycle reached a trough in 2009Q4, but stayed negative until the post-COVID outbreak. Only in 2022Q2 it turned positive again.

Regarding the financial cycles, we identify troughs in 1996Q4 for house prices and 1997Q1 for credit and a major expansion thereafter with peaks reached in 2007Q4 and 2008Q3, respectively. These estimates are consistent with the literature documenting the emergence of an asset price bubble in Ireland's real estate sector (Baudino et al., 2020), discussed in Section 2.2. Our estimates indicate that housing and credit cycles were broadly aligned in this boom phase until the onset of the GFC.

The GFC downturn lasted until 2013Q1, when the credit cycle exhibited another turning point. The trough in house prices cycle is estimated to have taken place somwehat later, in 2013Q4. Again, these estimates are in line with country reports indicating that the property market began to recover during 2013 (Baudino et al., 2020). However, the overall downward trend in credit persisted (right-hand side panel of Figure 2). Until to date, credit volumes have not returned to their pre-GFC levels.

In the post-COVID-19 period, we identify another turning point in credit and housing cycles, marking the onset of a more sustained upward phase, with the cycle estimated to have entered positive territory in 2022Q2. This shift may be associated with the fiscal and monetary support measures adopted in response to the COVID-19 crisis, including loan guarantees, credit moratoria, and liquidity facilities (Central Bank of Ireland, 2021; European Systemic Risk Board, 2020).

Our findings are consistent with recent empirical evidence on Irish cycles (Central Bank of Ireland, 2024; McQuinn et al., 2024; Yao, 2022; Egan and McQuinn, 2023). For

[7] These studies find that, among the major European economies, the German economy is unique in that it displays hardly any medium-term cycles. Huber et al. (2016) and Rünstler and Vlekke (2018), suggest that countries with a high rate of private home ownership appear to have larger and longer house price and credit cycles. The first study also finds some weak relationships with characteristics of national mortgage markets such as LTV ratios.

2024 on average, our UCM estimates GNI to be by 1.8 percent above its trend, national credit by 4.0, and house prices by 1.9 percent. This configuration indicates a ongoing financial cyclical expansion. However, as discussed in the following section, this is not necessarily suggestive of early warning signals.[8]

5 Early Warning Properties

Estimated cyclical components being above their historical mean are not necessarily indicative of increased macro-financial risks. To assess whether estimates of booms beyond a certain threshold are associated with an increased vulnerability in the Irish economy, this section evaluates the early warning properties of our estimated cyclical components against a variety of alternative models.

For such evaluation, it is important to replicate the information set that is available to policy-makers in real time. One important element in this respect is using estimates of cycles that are based on current and past information only. Accordingly, our early warning assessment relies on *one-sided* estimates, in contrast to those *full-sample* estimates that are usually reported in studies and use the full data series to estimate the cycle at a given point in time.

We start with defining a typology of crisis having affected Ireland in the past, and an assessment of the properties of one-sided estimates from our UCM and various alternative models. After a review of the respective criteria, we finally compare the early warning properties of the various models.

5.1 Systemic crisis and bank distress episodes in Ireland

To evaluate the early warning performance of the estimated cycles, this subsection outlines the episodes that the indicators are intended to signal.

First, we consider several crisis typologies that have affected Ireland in the past — namely currency, debt, and banking crises. Our systemic crises dataset draws on multiple sources, including Babecky et al. (2014), Laeven and Valencia (2020), and Baron and Dieckelmann (2021). For simplicity, we refer to this group collectively as *systemic crises*, distinguishing them from merely *bank distress events* [9]. In particular, the events reported in Baron and Dieckelmann (2021) — notably the 30% declines in bank equity observed in 1974, 1990, and 2016 — are not classified as systemic crises in the Irish case.[10]

Regarding currency crises identified by Babecky et al. (2014), a crisis episode appeared in Ireland in 1985Q1. However, as suggested by Baudino et al. (2020), the depreciation of the Irish pound against the US dollar extended beyond a single quarter.

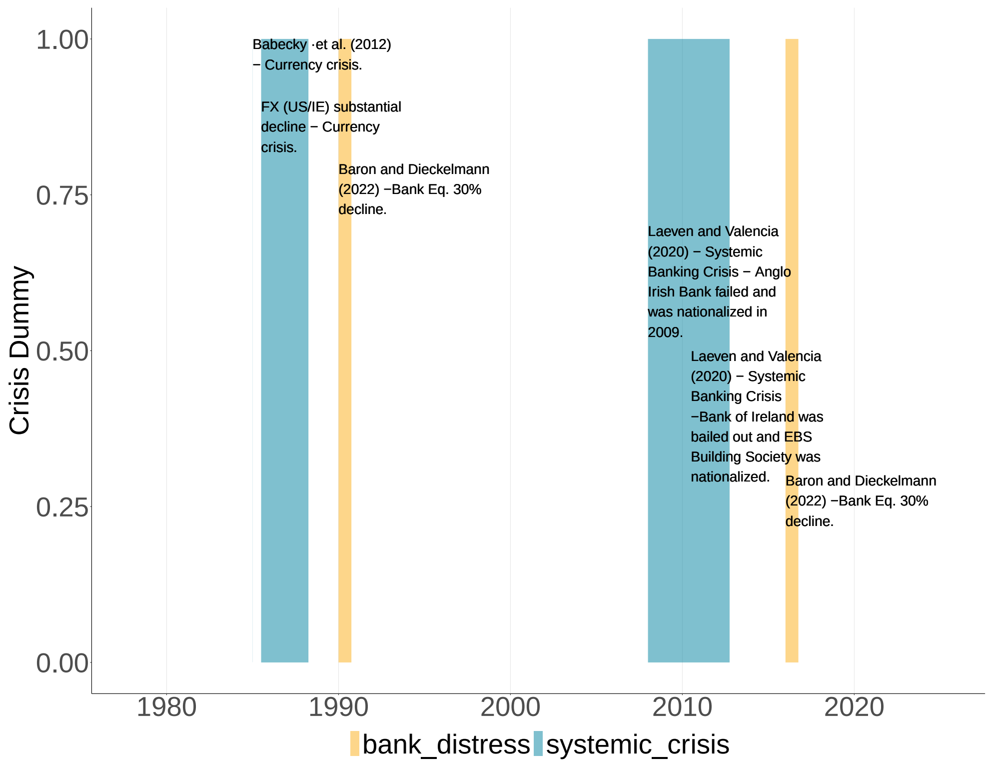
[8] In the case of national credit, the underlying trend is currently still negative. Hence, positive cyclical values should be interpreted as credit expanding relative to its declining long-term trend, rather than as an absolute increase in credit volumes.

[9] We adopt this broad labeling for illustrative purposes, acknowledging that formal definitions of systemic crises may vary. See, for instance, Laeven and Valencia (2020) for a comprehensive discussion.

[10] As the authors explicitly state, “there is no evidence of a banking panic”. Specifically, they report a significant bank equity decline in 1990 and 2016. These two episodes are therefore excluded from our systemic crisis series.

In particular, we observe a sustained quarter-on-quarter decline in the exchange rate from 1985Q3 to 1988Q2, as shown in Figure A.1 in Appendix 7. During this time, the exchange rate also remained below its long-term trend.[11] The second and third systemic crises occurred between 2008Q1 and 2010Q2, and from 2010Q3 to 2012Q4, respectively. These episodes are associated with the GFC and the subsequent European sovereign debt crisis. Figure 5 reports all systemic crisis events drawn from the aforementioned episodes.

FIGURE 5. Systemic crises in Ireland

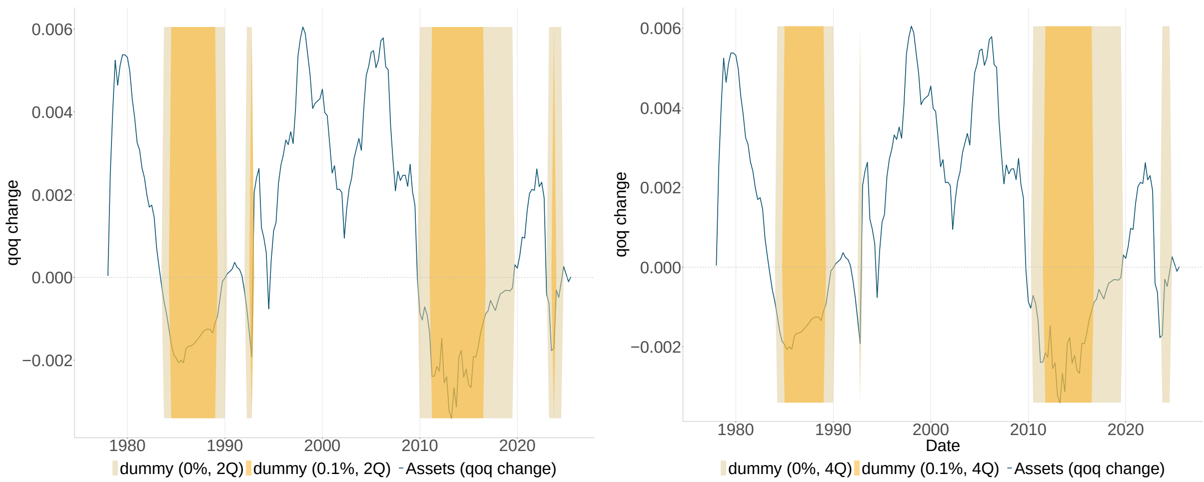


Second, we propose a proxy for domestic bank distress. In order for early warning indicators to be useful for macroprudential policy decisions, our objective is to identify measures that can inform the potential buildup of risks specifically within the Irish banking system. Specifically, we focus on the quarter on quarter variation of total assets held by Irish credit institutions that are issued by Irish residents. This approach seeks to isolate vulnerabilities originating within the domestic economy — such as excessive credit growth, misalignment in the housing market, or overheating of the economic activity — from those arising from exposures to the rest of the EU or global financial system. Accordingly, we exclude foreign assets, which may reflect external shocks rather than domestic-originated risks.[12]

[11] Computed using the Hodrick-Prescott filter with λ=1,600.

[12] Domestic total assets are sourced from the Central Bank of Ireland's (Table A.4: Aggregate Balance Sheet of Credit Institutions). We exclude loans to non-residents, holdings of securities issued by non-residents, and remaining assets held abroad. Public data are available from January 2003 onward. Pre-2003 values were provided by the Central Bank of Ireland but are not

FIGURE 6. Bank distress episodes in Ireland



Note: The panels show the constructed bank distress indicator based on quarter-on-quarter growth in domestic total assets held by Irish credit institutions. The left-hand panel signals distress if the growth rate remains below 0.0% or 0.1% for at least two consecutive quarters. The right-hand panel applies the same thresholds but requires at least four consecutive quarters of decline.

Our indicator of bank distress is a dummy that takes a value of one when the four-quarter moving average of quarter-on-quarter growth in domestic total assets remains below a given threshold for a minimum number of consecutive quarters and is zero otherwise. Both the threshold level and the required duration are set according to the policy-maker's degree of risk aversion. As an illustrative example, Figure 6 presents the results for two alternative specifications of the bank distress indicator. In the left-hand panel, distress is defined as at least two consecutive quarters with quarter-on-quarter growth below 0% or 0.1%, reflecting high risk aversion. The right-hand panel extends this definition to require at least four consecutive quarters below the same thresholds.[13]

Our indicator identifies episodes broadly consistent with those reported in Baron and Dieckelmann (2021). For instance, while the authors document a decline in bank equity between 1990Q1 and 1990Q4, our indicator flags distress periods based on domestic asset contractions occurring in 1990Q1, 1991Q2, and 1992Q2. Similarly, Baron and Dieckelmann report a decline in bank equity between 2016Q1 and 2016Q4, whereas our measure captures a sustained drop in domestic total assets extending until 2017Q4.

publicly available. Missing observations were estimated using a linear regression based on an AR(1) process and the one-period lag of the log of residential property prices index (See Table A.1 and Figure A.2).

[13]Applying this rule with a 0.1% threshold, we identify 37 quarters in which the four-quarter moving average of qoq asset growth remained below the threshold for at least four consecutive quarters, compared with 39 quarters when considering declines lasting at least two consecutive quarters.

5.2 Properties of one-sided filters

Efficient estimates of UCMs and univariate filters make use of both past and future observations to estimate trend and cyclical components. Following standard practice, the estimates presented in Section 3 represent such *full-sample* estimates.

By contrast, policymakers must rely solely on current and past information, when assessing cyclical positions in real time Such *one-sided* estimates are based on more limited information and therefore subject to higher uncertainty compared to the full-sample estimates. The associated difficulties in estimating output gaps as well as detecting financial booms and busts in real time are well documented in the literature (see Orphanides and Norden (2002) and Gadea Rivas and Perez-Quiros, 2015).[14]

A first step in assessing the reliability of one-sided estimates is comparing them with the full-sample estimates from the same model. In this section, we therefore inspect the properties of one-sided estimates from our benchmark model and from the Christiano-Fitzgerald and Hodrick-Prescott filters. Figures 7 and 8 compare one-sided and full-sample estimates from both models for national credit and house prices.

Following Orphanides and Norden (2002), Table 2 reports correlations between the one-sided and full-sample estimates and the root mean-squared error (RMSE) of their difference.

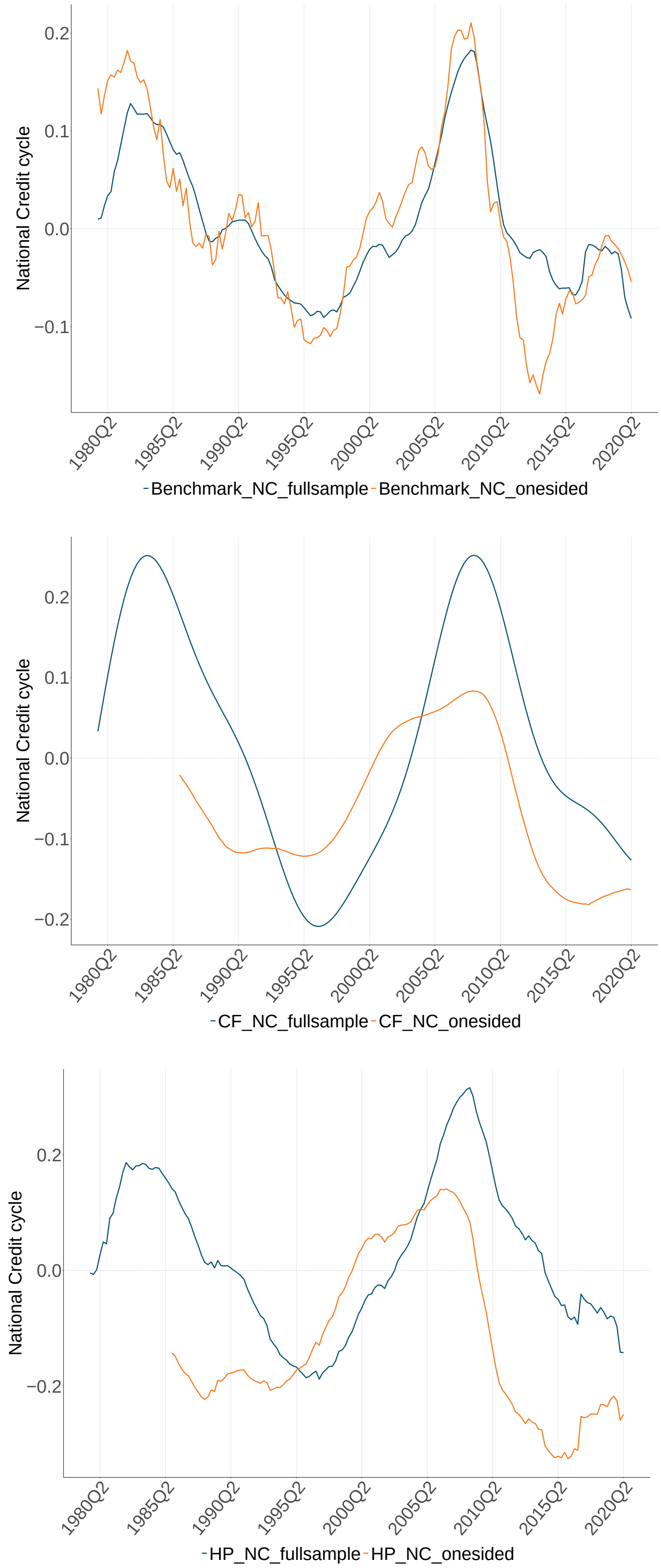
TABLE 2. One-Sided vs Full-Sample Estimates: Correlation and RMSE

	Benchmark	**CF Filter**	**HP Filter**
National Credit			
Correlation	0.877	0.704	0.403
RMSE	0.047	0.153	0.174
Standard deviation (full-sample)	0.071	0.143	0.135
House Prices			
Correlation	0.861	0.627	0.556
RMSE	0.055	0.212	0.119
Standard deviation (full-sample)	0.105	0.119	0.113

Note: The table reports the correlations between full-sample and one-sided estimates, the root mean squared error (RMSE) of their differences, and the standard deviations of full-sample estimates. The statistics are calculated over the period of 1985 Q1 to 2025 Q1.

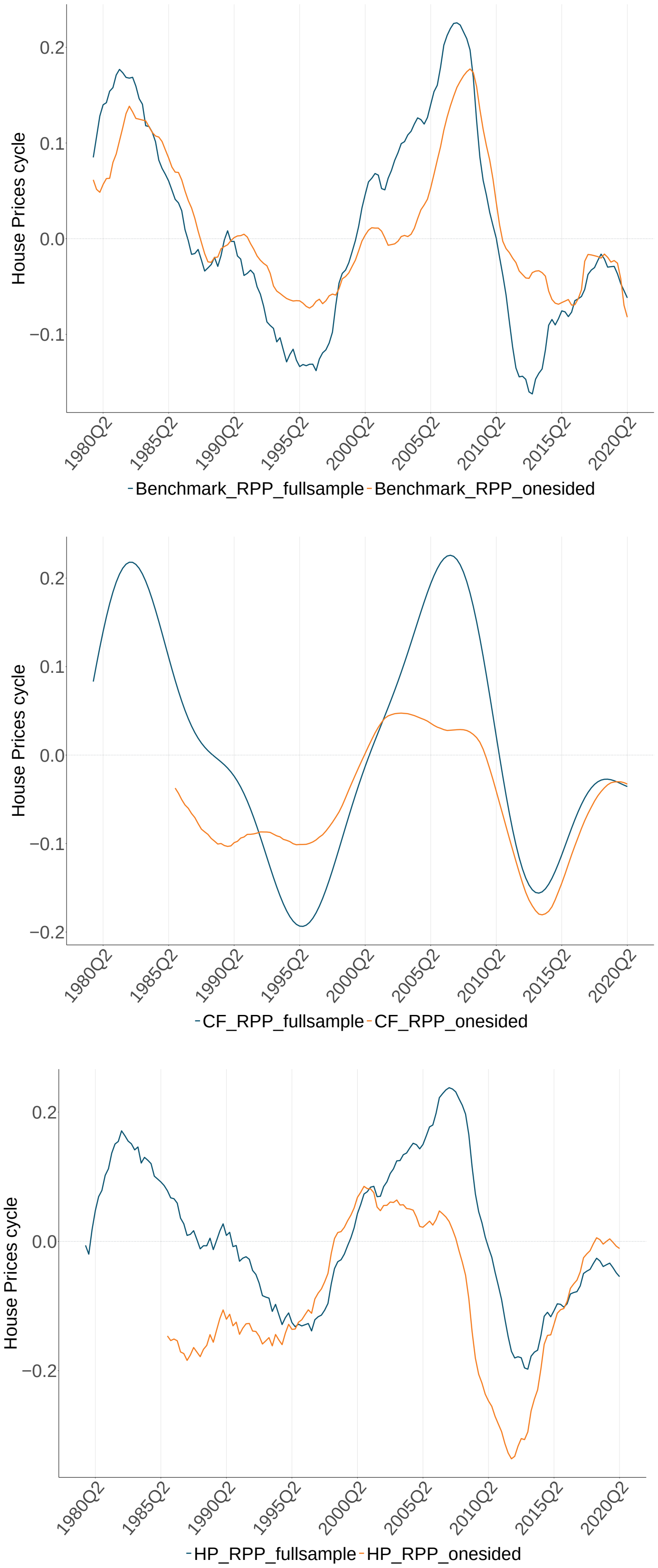
[14] The filters extract the trend as a weighted moving average of past and future observations. The weights extend symmetrically into the past and the future, but are necessarily cut off towards the end of the sample. It should be noted that we do not re-estimate UCM at each point in time.

FIGURE 7. One-Sided vs Full-Sample Estimates - National Credit



Note: Upper: Benchmark; Middle: Christiano Fitzgerald (CF); Lower: Hodrick Prescott (HP).

FIGURE 8. One-Sided vs Full-Sample Estimates - House Prices



Note: Upper: Benchmark; Middle: Christiano Fitzgerald (CF); Lower: Hodrick Prescott (HP).

In line with Rünstler and Vlekke (2018), we find that the reliability of one-sided estimates from the benchmark model surpasses both the Christiano–Fitzgerald (CF) and Hodrick–Prescott (HP) filters. Correlations are highest for the benchmark model, at 0.88 for national credit and 0.86 for house prices, compared to the CF filter (0.70 and 0.63) and the HP filter (0.40 and 0.56). Regarding the size of revisions, the benchmark model also clearly outperforms the CF and HP filters, with RMSEs of 0.047 and 0.055 versus 0.153 and 0.212 for the CF filter, and 0.174 and 0.119 for the HP filter. For the two univariate filters, the size of revisions turns out to be of the same scale as the one of the full-sample estimates.

5.3 Performance criteria and optimal thresholds

In this subsection, we evaluate the early warning performance of our estimated cycles across different estimation methods. Specifically, we consider the benchmark model for national credit (Benchmark_NC), house prices (Benchmark_RPP), and their composite indicator (Benchmark_comp).[15] As alternatives, we examine one-sided univariate filters, namely the Hodrick–Prescott filter (HP_NC and HP_RPP) and the Christiano–Fitzgerald band-pass filter (CF_NC and CF_RPP), as well as model-based approaches: a VECM following Galán and Mencia (2018) (VEC_GM2_NC)[16] and the multivariate unobserved-components model of O'Brien and Velasco (2020) (OV_NC) for national credit.

Starting from the systemic crisis events reported in Figure 5, we construct a dummy variable. As in Drehmann and Juselius (2014), our dependent variable ($SysCE_t$) is set to one during pre-crisis periods, and zero for observations that are not followed by a crisis within the defined horizon (tranquil periods).[17]

To inform policy decisions, the estimated cyclical indicators can be transformed into binary early warning signals. As a first step, we rescale the estimated cycles to lie between 0 and 1 to facilitate interpretation and comparability across methods.

These signals can ex-post be classified as true positives, false positives, true negatives, or false negatives, as shown in Table 3. False negatives (type I errors) occur when no signal is issued during a pre-crisis window (missed crises), whereas false positives (type II errors) occur when a signal is issued outside the window (false alarm).

Adjusting the classification threshold τ involves a trade-off between the two error types: a higher threshold reduces the number of signals, lowering both true and false positives. The optimal threshold depends on the forecast user's loss function. A commonly used approach, following Alessi and Detken (2011), is to select the threshold that maximizes the *relative usefulness* function, which weighs type I and type II errors according to the policymaker's relative preference parameter μ.

[15] As described in Section 3.3, the composite indicator — aimed at representing the financial cycle — is computed as the simple average of the standardized credit and house price cycles.

[16] We also perform the early warning assessment on the customized VECM (VEC_GM1_NC). For parsimony, however, we do not report its results here, as the VEC_GM2_NC specification displays superior early-warning properties.

[17] Given the typical long duration of financial cycles, we define the pre-crisis period as the twelve quarters immediately preceding the onset of each systemic crisis.

TABLE 3. Contingency Matrix for Early Warning Evaluation

Predicted Class	Pre-crisis Period (C)	Tranquil Period ($\neg C$)
Signal (S)	True Positive (TP): Correct Call	False Positive (FP): False Alarm
No Signal (¬S)	False Negative (FN): Missed Crisis	True Negative (TN): Correct Silence

Note: This contingency matrix follows the structure proposed by Holopainen and Sarlin (2017).

We assess early warning performance using three complementary metrics: the area under the ROC curve (AUC), the F_1 score, and relative usefulness. The AUC summarizes model performance across all possible classification thresholds. It plots the trade-off between type I and type II errors in the receiver operating characteristic (ROC) measures the overall discriminative power of the model. AUC values range from 0 to 1, where 0.5 implies no predictive power and 1 corresponds to perfect classification (Drehmann and Juselius, 2014). According to the standard literature, a perfect indicator has an AUROC of 1, whereas an uninformative indicator scores 0.5.

Figure 9 summarizes the AUC results. The right-hand panel shows that, for the house price series, the benchmark model (Benchmark_RPP) outperforms the composite financial indicator (Benchmark_comp), the Christiano–Fitzgerald filter (CF_RPP), and the Hodrick–Prescott filter (HP_RPP). In the left-hand panel, focusing on national credit, the composite financial cycle (Benchmark_comp) performs best, ahead of both the benchmark national credit cycle (Benchmark_NC) and the Christiano–Fitzgerald filter (CF_NC). By contrast, the Hodrick–Prescott filter (HP_NC), the VEC model (VEC_GM2_NC), and the UCM of O'Brien and Velasco (2020) (OV_NC) yield the lowest AUC values.

The F_1 score, by contrast, focuses solely on the model's ability to predict crisis periods. It is defined as the harmonic mean of precision as follows:

$$F_1 = \frac{TP}{TP + \frac{1}{2}(FP + FN)}.$$

This metric increases with the proportion of correctly predicted crises (true positives) relative to incorrect signals (false alarms and missed crises). A perfect predictor yields $F_1 = 1$, while a model that fails to predict any crisis yields $F_1 = 0$. A known limitation of the F_1 score is that it ignores correct predictions of tranquil periods (true negatives), potentially underestimating the value of models that avoid unnecessary policy interventions (Powers, 2020).

Relative usefulness (U_r), proposed by Alessi and Detken (2011), evaluates the gain of the model over a naive decision rule that either always or never issues a signal. It is defined as

$$U_r(\mu) = 1 - \frac{L(\mu)}{\min(\mu, 1-\mu)}, \tag{8}$$

where $L(\mu)$ is the policymaker's loss function, given by

$$L(\mu) = \mu \cdot \frac{FN}{TP + FN} + (1 - \mu) \cdot \frac{FP}{TN + FP}. \tag{9}$$

Parameter $\mu \in [0, 1]$ reflects the relative cost of missing a crisis versus issuing a false alarm. A value of $U_r = 1$ implies perfect classification, while $U_r = 0$ indicates that the model performs no better than the naive benchmark. For our baseline results, we follow the standard approach and set $\mu = 0.80$, assigning balanced preferences for both types of classification errors (see Sarlin, 2013).

FIGURE 9. Area under the curve

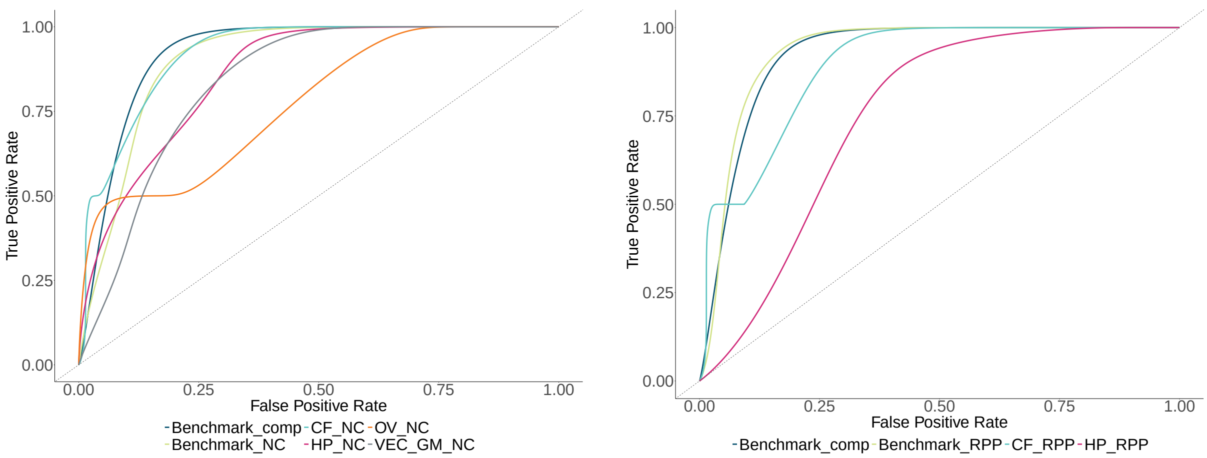


Table 4 reports the AUC, F_1, and relative usefulness metrics, along with the deviation of each model relative to the composite financial indicator. In the case of these deviations, values above one indicate that a model outperforms the composite, while values below one reflect under-performance. Overall, the table shows that the benchmark estimates, together with the Christiano–Fitzgerald national credit cycle, deliver the strongest early-warning performance, whereas the other approaches consistently under-perform. Nevertheless, as discuss in Section 5.2, the Christiano–Fitzgerald filter does not exhibit real-time properties as robust as those of our benchmark model. Among the lowest-performing indicators, the house price cycle estimated with the Hodrick–Prescott filter exhibits the lowest relative usefulness.

Following (Beutel et al., 2019), we compute the optimal thresholds for all estimated cycles across methods by minimizing the policymaker's loss function (equation 9) over the full set of candidate cut-off values, each associated with corresponding true and false positive rates. When multiple thresholds yield the same minimum loss, we apply a conservative tie-breaking rule and select the lowest threshold.

In Figure 10, we report the benchmark composite financial indicator, scaled between 0 and 1, along with its corresponding optimal threshold targeting systemic crises. To define the lower and upper bounds, we employ the standard deviations across the optimal thresholds obtained when the indicators targets different episodes of bank distress (see Figure 6). We find that, at the present, the benchmark benchmark composite financial cycle lies well below the lower bound, indicating an absence of early warning signals for systemic crises, aiding further policy assessment.

TABLE 4. Early warning performance metrics

	Indicator			Relative Deviation		
	AUC	**F1**	**Rel. useful**	**AUC**	**F1**	**Rel. useful**
Benchmark_NC	0.903	0.924	0.760	0.977	1.010	1.030
Benchmark_RPP	0.930	0.915	0.740	1.010	0.997	1.000
Benchmark_comp	0.924	0.918	0.740	1.000	1.000	1.000
HP_NC	0.862	0.846	0.500	0.933	0.921	0.676
HP_RPP	0.749	0.796	0.365	0.811	0.867	0.493
CF_NC	0.921	0.946	0.833	0.998	1.030	1.130
CF_RPP	0.891	0.909	0.708	0.965	0.990	0.958
OV_NC	0.773	0.789	0.469	0.837	0.859	0.634
VEC_GM_NC	0.838	0.875	0.583	0.907	0.953	0.789

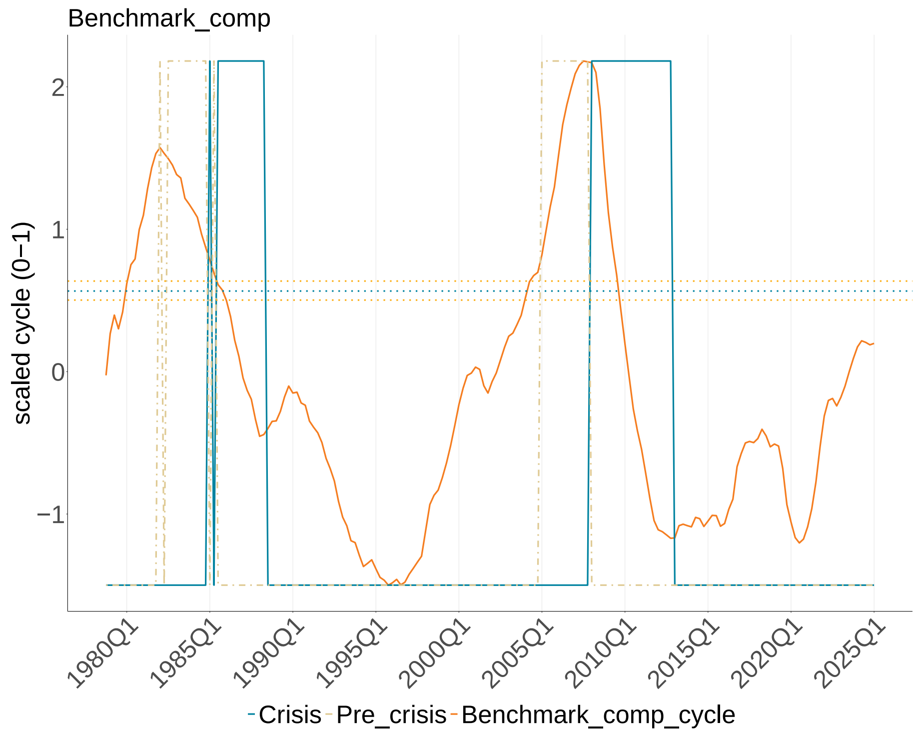
Note: Metrics are based on the three-year pre-crisis period preceding the systemic crisis episodes shown in Figure 6. Columns 'Relative Deviation' refer to the absolute value relative to the composite indicator from the benchmark model.

In Appendix 7, we report analogous figures for the estimated cycles and their optimal thresholds under alternative estimation methods (see Figures A.3-A.10). Across all alternative specifications, the current value of the early warning indicator remains below the lower bound of the corresponding optimal thresholds.

Figures A.11 to A.13 in Appendix 7 display the pseudo real-time estimates. To construct these, we compute the full-sample benchmark indicators for each estimation window, starting with the sample period from 1975Q4 to 100 quarters later (2000Q3) and then expanding the window by one quarter at a time until reaching 2022Q1. As follows, this procedure yields 85 estimates for each indicator. We also report the thresholds obtained from the indicators estimated over the entire sample period (1975Q4–2022Q1), following the procedure described above.[18] Using these thresholds, after the pronounced upward phase in the credit and house price cycles, we observe that an alarm could have been triggered in the early 2000s, although only for two consecutive quarters. More importantly, three years before the GFC outbreak, the indicators would have persistently signaled a systemic crisis over several consecutive quarters. Thus, in line with the relative usefulness metric, our benchmark indicators are subject to occasional false alarms, but retain a low probability of missing a systemic crisis—an aspect of particular importance for policymaking decisions.

[18]For simplicity, thresholds are based on the entire sample period; otherwise, each of the 85 estimates would imply a different threshold and fewer crisis periods for evaluation.

FIGURE 10. Crisis signals from the benchmark composite financial cycle



Note: The benchmark composite financial cycle and its optimal threshold are re-scaled to be in between 0 and 1. The blue dashed horizontal line corresponds to the optimal threshold based on the minimum loss function (see Equation 9). The orange dashed lines represent the upper and lower bounds, computed as one standard deviation around the optimal thresholds obtained when the indicator targets different episodes of bank distress. The lower (upper) bound is computed as the minimum (maximum) between the corresponding bounds of the credit and house price cycles, in order to maximize the stringency of early warning signals. The vertical lines denote the systemic crisis and pre-crisis periods.

6 Conclusion

This paper applies the multivariate unobserved components model proposed in Rünstler and Vlekke (2018) to jointly estimate the cyclical and trend components of output, credit, and house prices in Ireland. Our results confirm a well-established finding in the literature: financial cycles are significantly longer than business cycles. In the Irish case, we estimate the duration of the credit and house price cycles to be approximately 15 years compared to 8.5 years for the business cycle.

We find that the house price cycles estimated from the benchmark model exhibit strong early warning properties for systemic financial crises, which are superior to alternative estimates. In particular, the benchmark estimates and the Christiano-Fitzgerald filter outperform other indicators in anticipating crises. However, when it comes to the reliability of real-time estimates, the benchmark cycles perform better. These findings reinforce the suitability of this method for supporting counter-cyclical macroprudential policy decisions in real time.

Our results support the view that flexible, data-driven multivariate frameworks offer substantial advantages for macroprudential surveillance, including in the context of real-time estimation. Future research could extend this framework to incorporate cross-country synchronization of financial cycles, explore interactions between macroprudential and monetary policy, and examine the role of borrower-based measures in shaping the long-term trends of house prices.

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7 Appendix

7.1 Complementary Tables and Figures

TABLE A.1. Data sources

Variable	Source	Frequency	ID
Modified Gross National Income (GNI)	CSO	Annual	NA001
Residential Property Price Index	CSO	Monthly	HPM09
Credit to Households (outstanding)	ECB	Quarterly	Link [a]
Credit to Non-Financial Corporations (outstanding)	CBI	Quarterly	Link[b]
Consumer Price Index (All Items)	CSO	Monthly	CPM01
Unemployment Rate Seasonally Adjusted	CSO	Monthly	MUM01
Modified Domestic Demand (MDD)	CSO	Quarterly	NAQ05
Household Loan Rates	CBI	Monthly	Link[c]
Domestic total assets	CBI	Monthly	Link[d]

Note: Central Statistics Office (CSO); European Central Bank (ECB); Central Bank of Ireland (CBI). Some historical series are not publicly available and were provided by the Central Bank of Ireland. These include quarterly GNI (pre-1998Q1), national credit (pre-2002Q4) and residential property prices (pre-2004Q4), and monthly household loan rates (pre-2003Q1) and domestic total assets (pre-2002Q1).

[a] QSA.Q.N.IE.W0.S1M.S1.N.L.LE.F4.T._Z.XDC._T.S.V.N._T.

[b] Central Bank of Ireland, Data & Analysis, Credit and Banking Statistics, Bank Balance Sheets, Table A.1 Summary Irish Private Sector Credit and Deposits.

[c] Central Bank of Ireland, Data & Analysis, Credit and Banking Statistics, Retail Interest Rates, Table B.1.2 Retail Interest Rates - Loans, Outstanding Amounts.

[d] Central Bank of Ireland, Data & Analysis, Credit and Banking Statistics, Bank Balance Sheets, Table A.4: Aggregate Balance Sheet of Credit Institutions.

TABLE A.2. Descriptive statistics

Name	Description	Mean	SD	Max	Min
GNI	Logarithms, seasonally adjusted, real terms	1.8184	0.4652	2.5120	0.7101
National credit	Logarithms, seasonally adjusted, real terms	1.7078	0.6354	2.5214	0.2918
House prices	Logarithms, seasonally adjusted, real terms	1.7297	0.4005	2.2886	0.7933
Household loan rates	Real terms; real terms	2.3768	1.1026	4.6545	1.0067
CPI	Year-on-year log change	4.1531	4.7929	21.0823	-6.3236

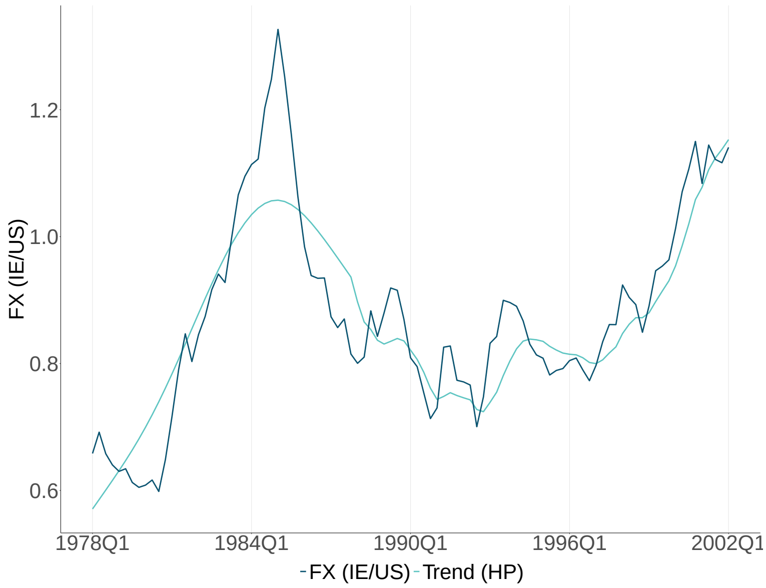
Note: The sample period extends from 1975Q4 to 2025Q1. Values are expressed in real terms using the Consumer Price Index all Items (CPI) with base year 2025Q1 (see Table A.1). The household loan interest rate series is monthly, aggregated to quarterly by arithmetic mean.

TABLE A.3. Cycle lengths and volatility across selected countries

Country / Statistic	Business	Credit	House Prices
Estimated Cycle Length (years)			
Ireland (IE)	8.53	14.75	15.35
United States (US)	8.74	11.79	12.11
United Kingdom (UK)	13.48	15.84	16.48
Germany (DE)	6.33	6.19	7.11
Italy (IT)	9.24	13.14	13.34
EU17 Average	11.67	14.16	13.83
Standard Deviation of cycles			
Ireland (IE)	0.03	0.07	0.10
EU17 Average	0.03	0.11	0.08
EU17 75th Percentile	0.04	0.14	0.09
EU17 25th Percentile	0.01	0.08	0.07

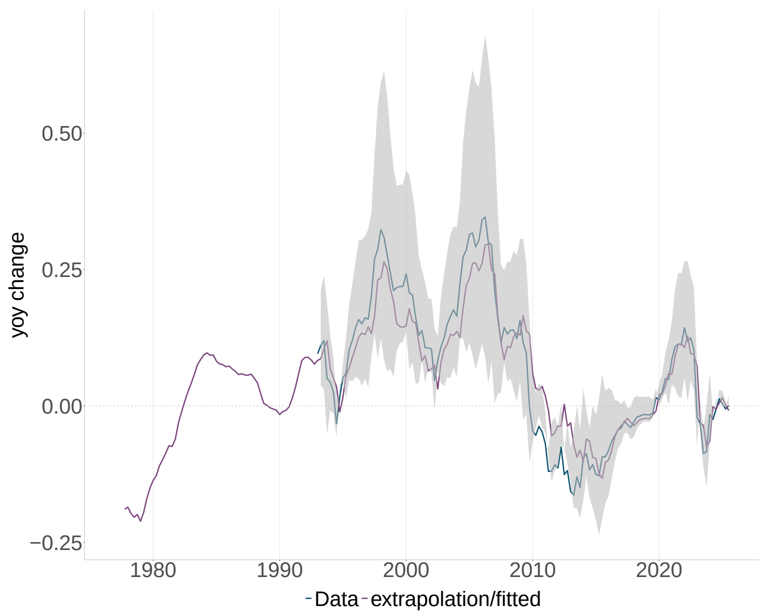
Note: Results for Ireland are based on the authors' own estimations, while results for other countries are taken from Rünstler and Vlekke (2018); Rünstler et al. (2018).

FIGURE A.1. Currency crisis — Irish pounds per US dollar



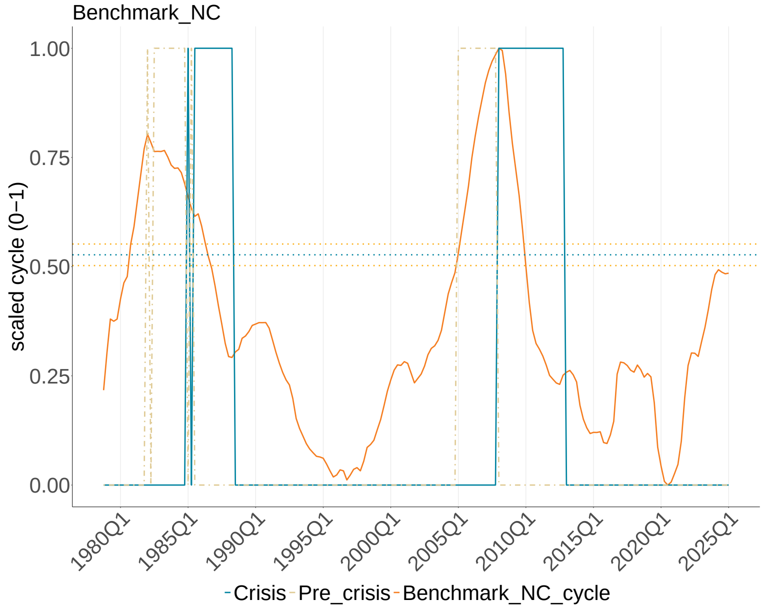
Note: The trend is estimated using a recursive Hodrick-Prescott filter with a smoothing parameter $\lambda = 1600$. Source: FRED, US Dollar Exchange Rate: Average of Daily Rates: National Currency: USD for Ireland, Euro, Quarterly, Not Seasonally Adjusted (ID: `CCUSMA02IEQ618N`). Available at https://fred.stlouisfed.org/series/CCUSMA02IEQ618N.

FIGURE A.2. Domestic Assets hold by Irish domestic credit institutions



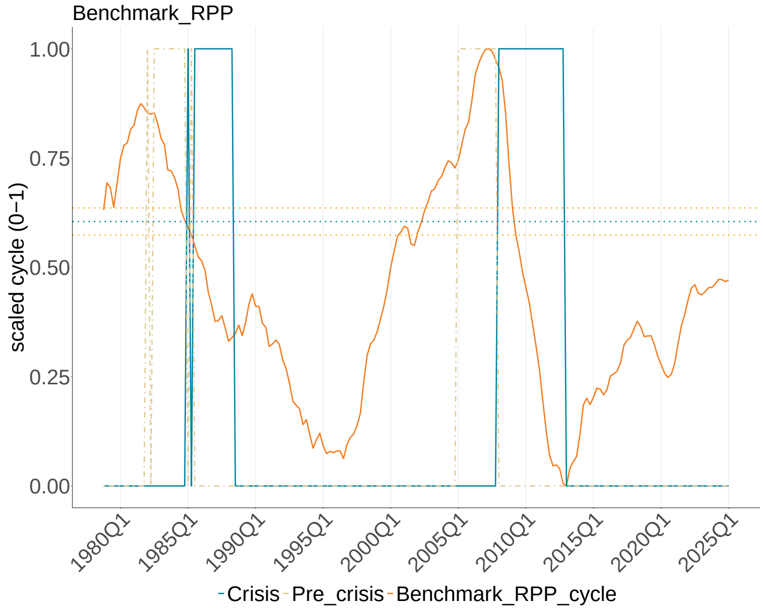
Note: Domestic total assets are sourced from the Central Bank of Ireland's (Table A.4: Aggregate Balance Sheet of Credit Institutions). We exclude loans to non-residents, holdings of securities issued by non-residents, and remaining assets held abroad. Public data are available from January 2003 onward. Pre-2003 values were provided by the Central Bank of Ireland but are not publicly available. Missing values were extrapolated using a linear regression $assets_{yoy,t} = \alpha + \beta_1 assets_{yoy,t-1} + \beta_2 log(hp)_{yoy,t-1} + \epsilon_t$ (see sources in Table A.1). The shaded area represents the 95% confidence interval. The model fit for this extrapolation attains $R^2 = 0.888$ and adjusted $R^2 = 0.882$.

FIGURE A.3. Crisis signals from the benchmark national credit cycle



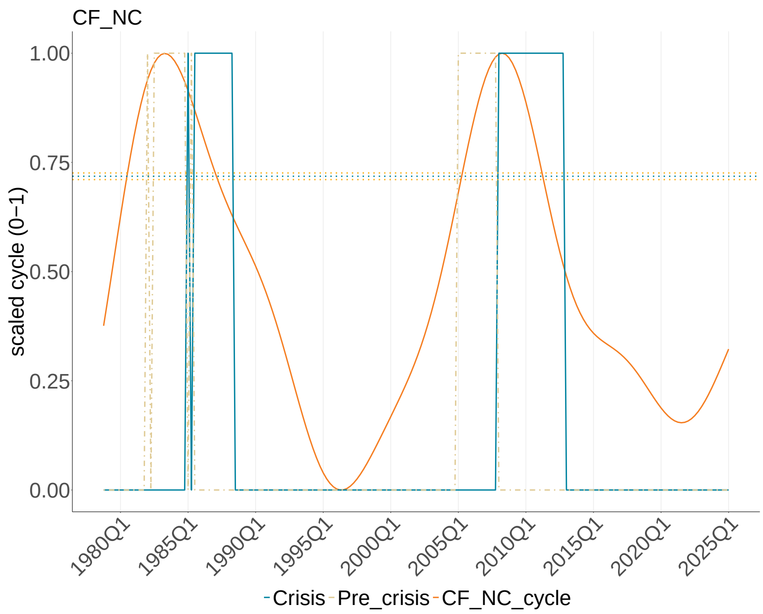
Note: The benchmark national credit cycle and its optimal threshold are scaled between 0 and 1. The blue dashed horizontal line corresponds to the optimal threshold based on the minimum loss function (see Equation 9). The orange dashed lines represent the upper and lower bounds, computed as one standard deviation around the optimal thresholds obtained when the indicator targets different episodes of bank distress. The vertical lines denote the systemic crisis and pre-crisis periods.

FIGURE A.4. Crisis signals from the benchmark house prices cycle



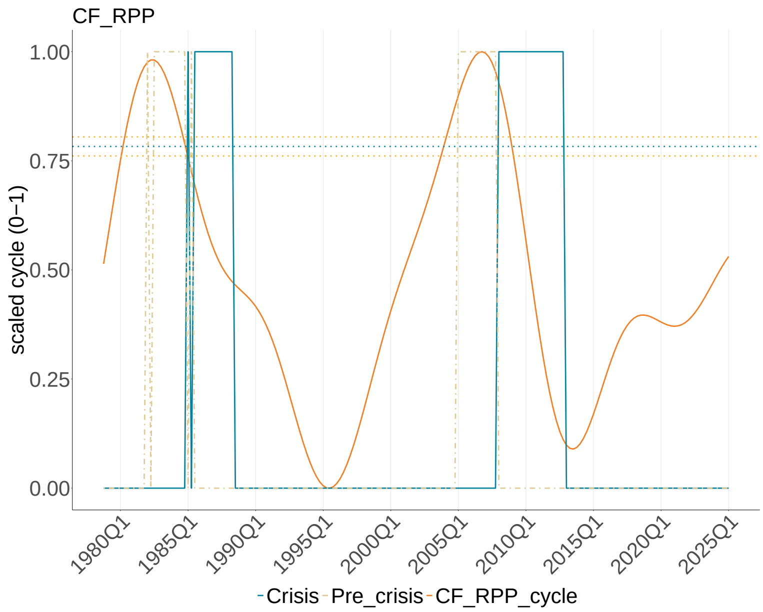
Note: The benchmark house prices cycle and its optimal threshold are scaled between 0 and 1. The blue dashed horizontal line corresponds to the optimal threshold based on the minimum loss function (see Equation 9). The orange dashed lines represent the upper and lower bounds, computed as one standard deviation around the optimal thresholds obtained when the indicator targets different episodes of bank distress. The vertical lines denote the systemic crisis and pre-crisis periods.

FIGURE A.5. Crisis signals from national credit cycle - Christiano-Fitzgerald



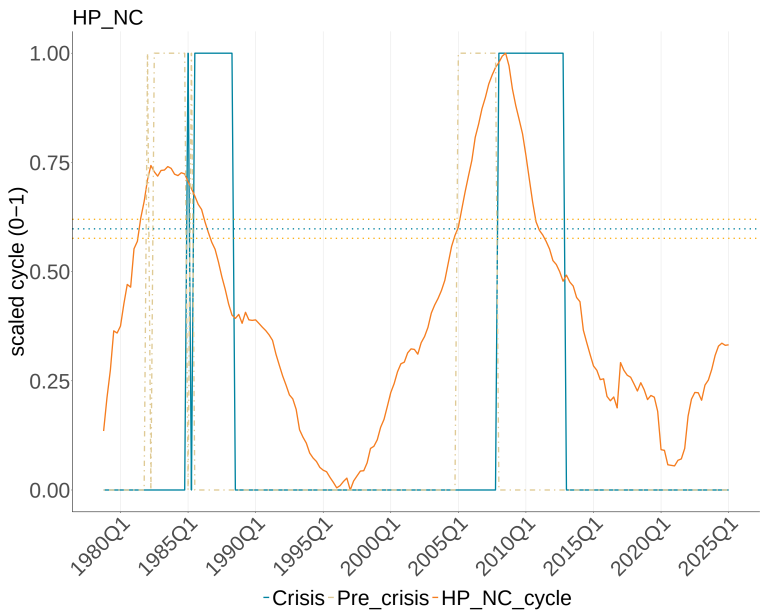
Note: The national credit cycle is estimated with the Christiano-Fitzgerald band-pass filter with frequency bands between 32 and 120 quarters. The cycle and its optimal threshold are scaled between 0 and 1. The blue dashed horizontal line corresponds to the optimal threshold based on the minimum loss function (see Equation 9). The orange dashed lines show the bounds, defined as one standard deviation around the optimal thresholds across bank distress episodes. The vertical lines denote the systemic crisis and pre-crisis periods.

FIGURE A.6. Crisis signals from the house prices cycle - Christiano-Fitzgerald



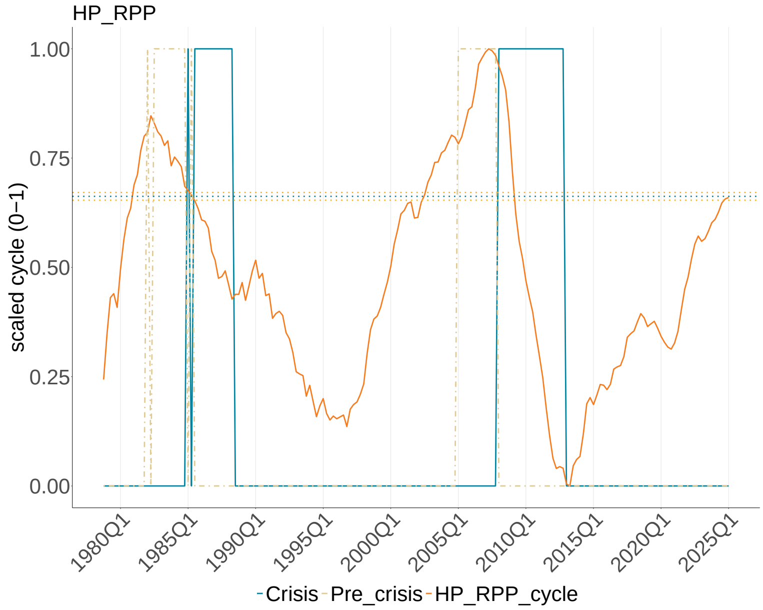
Note: The house prices cycle is estimated with the Christiano-Fitzgerald band-pass filter with frequency bands between 32 and 120 quarter. The cycle and its optimal threshold are scaled between 0 and 1. The blue dashed horizontal line corresponds to the optimal threshold based on the minimum loss function (see Equation 9). The orange dashed lines show the bounds, defined as one standard deviation around the optimal thresholds across bank distress episodes. The vertical lines denote the systemic crisis and pre-crisis periods.

FIGURE A.7. Crisis signals from the national credit cycle - Hodrick-Prescott



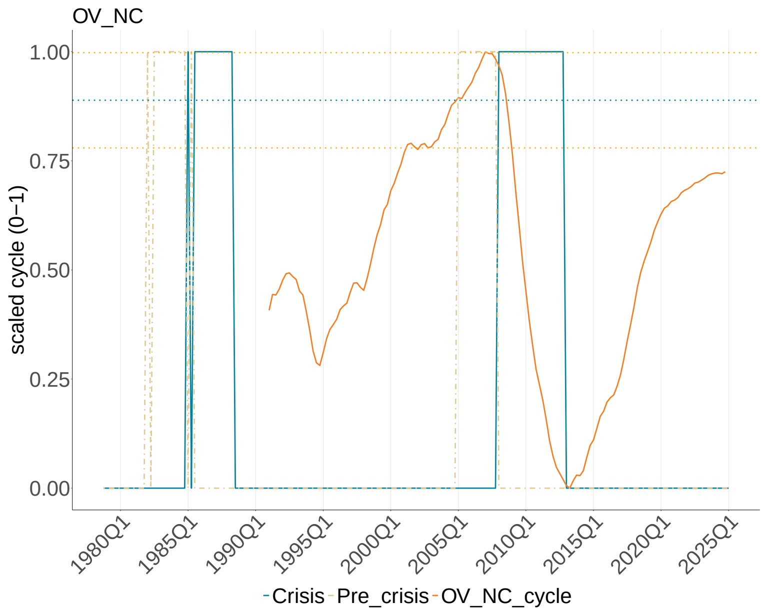
Note: The national credit cycle is estimated with a Hodrick-Prescott filter with λ=400,000, as recommended in (ESRB, 2014). The cycle and its optimal threshold are scaled between 0 and 1. The blue dashed horizontal line corresponds to the optimal threshold based on the minimum loss function (see Equation 9). The orange dashed lines show the bounds, defined as one standard deviation around the optimal thresholds across bank distress episodes. The vertical lines denote the systemic crisis and pre-crisis periods.

FIGURE A.8. Crisis signals from the house prices cycle - Hodrick-Prescott



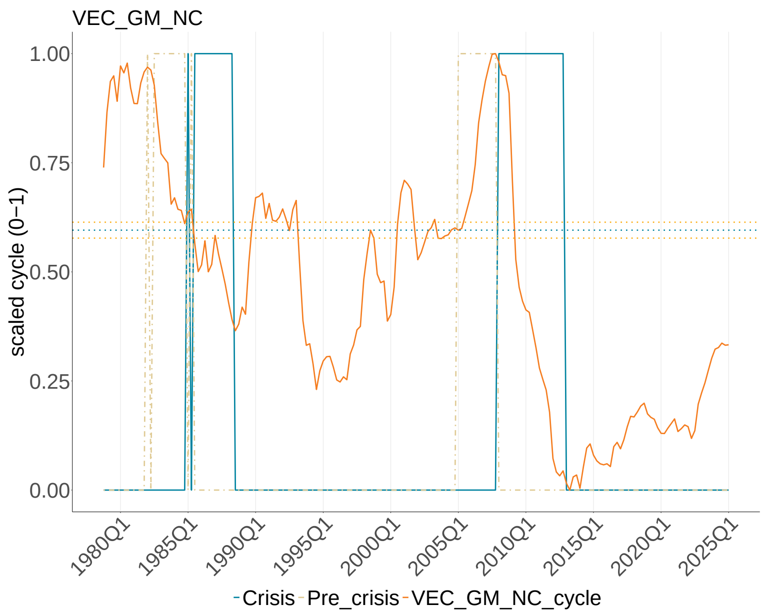
Note: The house prices cycle is estimated with a Hodrick-Prescott filter with λ=400,000, following the same recommendation as in ESRB, 2014 for the credit cycle. The cycle and its optimal threshold are scaled between 0 and 1. The blue dashed horizontal line corresponds to the optimal threshold based on the minimum loss function (see Equation 9). The orange dashed lines show the bounds, defined as one standard deviation around the optimal thresholds across bank distress episodes. The vertical lines denote the systemic crisis and pre-crisis periods.

FIGURE A.9. Crisis signals from the national credit cycle - O'Brien and Velasco (2020)



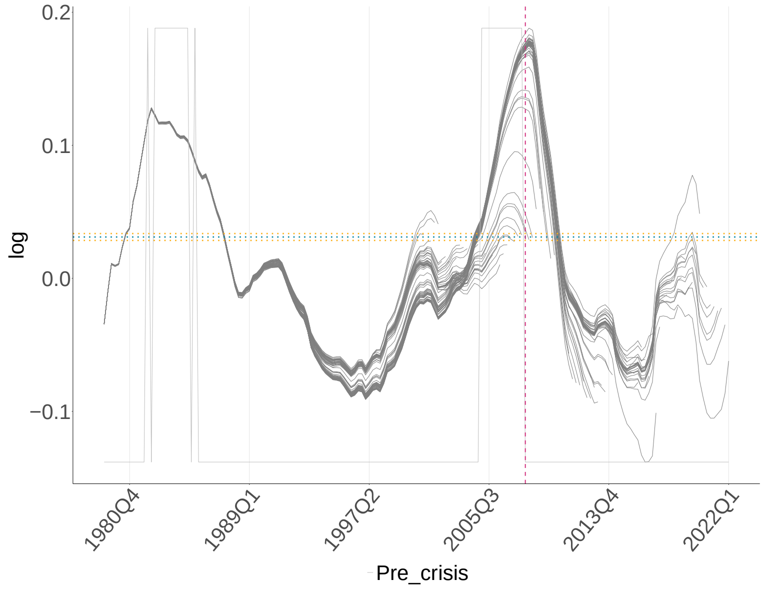
Note: The national credit cycle is estimated as in O'Brien and Velasco (2020). The cycle and its optimal threshold are scaled between 0 and 1. The blue dashed horizontal line corresponds to the optimal threshold based on the minimum loss function (see Equation 9). The orange dashed lines show the bounds, defined as one standard deviation around the optimal thresholds across bank distress episodes. The vertical lines denote the systemic crisis and pre-crisis periods.

FIGURE A.10. Crisis signals from the national credit cycle - Galán and Mencia (2018)



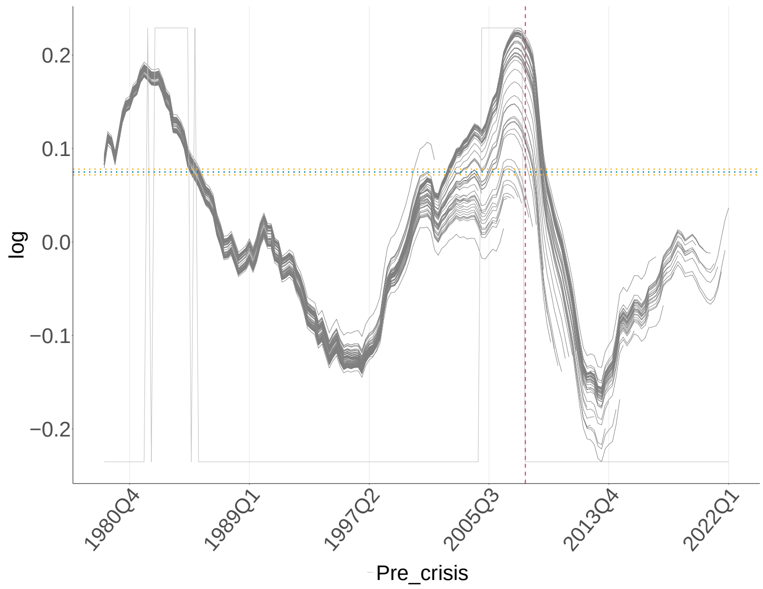
Note: The national credit cycle is estimated as in Galán and Mencia (2018). The cycle and its optimal threshold are scaled between 0 and 1. The blue dashed horizontal line corresponds to the optimal threshold based on the minimum loss function (see Equation 9). The orange dashed lines show the bounds, defined as one standard deviation around the optimal thresholds across bank distress episodes. The vertical lines denote the systemic crisis and pre-crisis periods.

FIGURE A.11. Pseudo Real time properties - national credit cycle



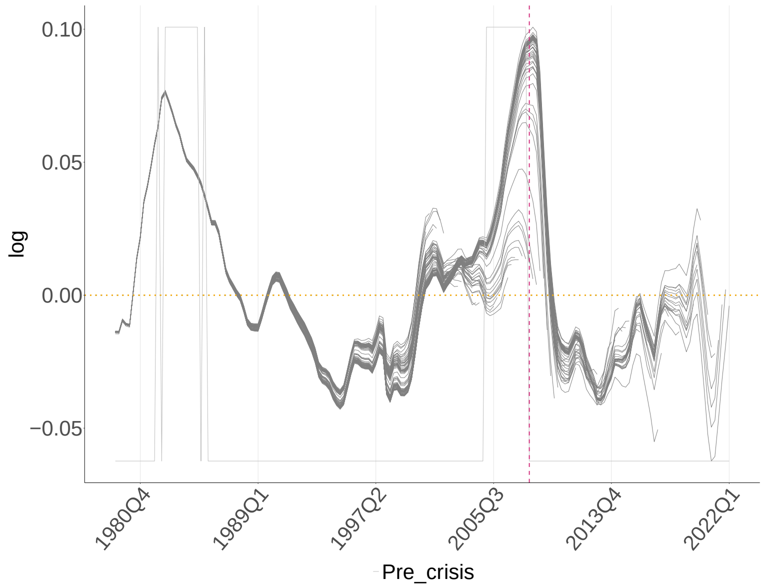
Note: Estimated with the benchmark model (full-sample estimates). Cycle is scaled between 0 and 1. The blue dashed horizontal line corresponds to the optimal threshold based on the minimum loss function (see Equation 9). The orange dashed lines show the bounds, defined as one standard deviation around the optimal thresholds across bank distress episodes. The vertical dashed line corresponds to the global financial crisis outbreak.

FIGURE A.12. Pseudo Real time properties – house prices cycle



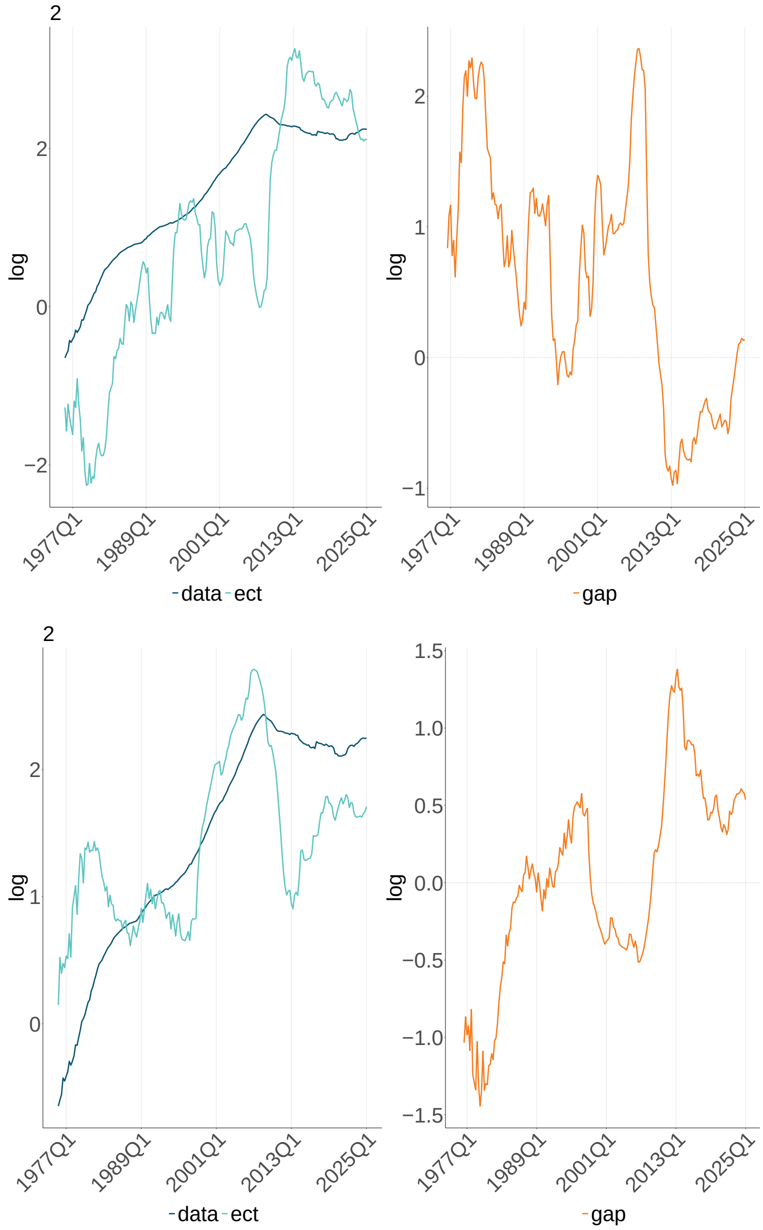
Note: Estimated with the benchmark model (full-sample estimates). Cycle is scaled between 0 and 1. The blue dashed horizontal line corresponds to the optimal threshold based on the minimum loss function (see Equation 9). The orange dashed lines show the bounds, defined as one standard deviation around the optimal thresholds across bank distress episodes. The vertical dashed line corresponds to the global financial crisis outbreak.

FIGURE A.13. Pseudo Real time properties – business cycle



Note: Estimated with the benchmark model (full-sample estimates). Cycle is scaled between 0 and 1. The blue dashed horizontal line corresponds to the optimal threshold based on the minimum loss function (see Equation 9). The orange dashed lines show the bounds, defined as one standard deviation around the optimal thresholds across bank distress episodes. The vertical dashed line corresponds to the global financial crisis outbreak.

FIGURE A.14. Estimated Error Correction Term and Cycle - VECM



Note: Left panel: estimated Error correction term and data; Right panel: estimated cycle. Upper panel: specification following Galán and Mencia (2018); lower panel: under the customized specification, where the loan interest rates are removed.