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## Identifying macrofinancial risk regimes in Malta

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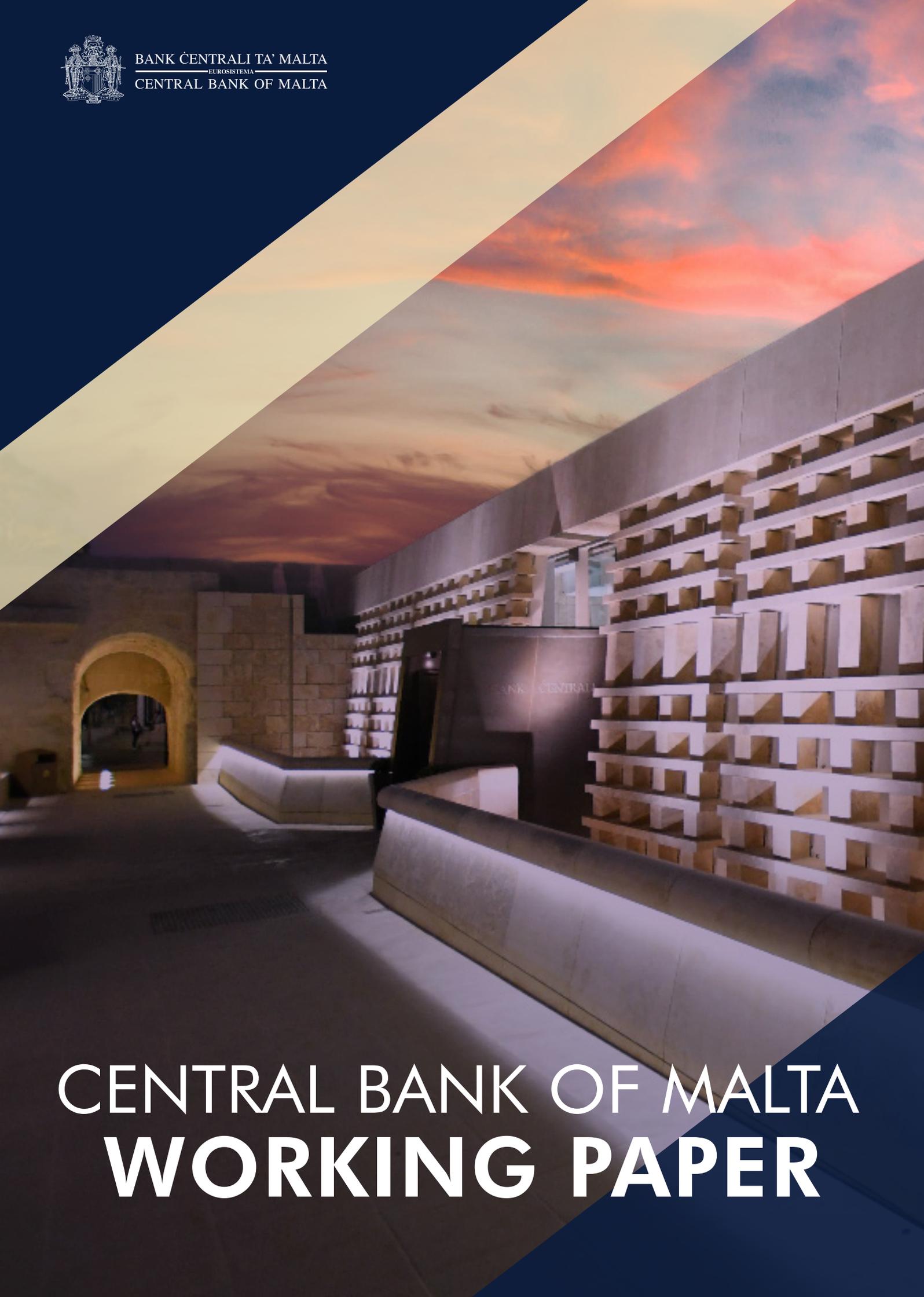
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# CENTRAL BANK OF MALTA WORKING PAPER



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EUROSISTEMA  
CENTRAL BANK OF MALTA

## Identifying macrofinancial risk regimes in Malta\*

William Gatt<sup>†</sup>

Sarah Vella<sup>‡</sup>

WP/05/2025

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**The views expressed in this paper are the authors' own and do not necessarily reflect the views of the Central Bank of Malta.** Correspondence: [www.centralbankmalta.org/contact-us](http://www.centralbankmalta.org/contact-us)

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### **Abstract**

The withdrawal of public sector intervention from Malta's housing market commenced in the early 1990s, while financial markets were liberalised in 1994. These developments were likely behind the significant expansion in credit and house price appreciation experienced over the past two decades, reflecting a market-driven process of financial deepening. However, contrary to the experience of other countries, Malta has not experienced a financial crisis since. Nevertheless, it has experienced episodes of high financial stress in which leverage and house price growth peaked. This paper builds an early warning system which formalises the stages of the Maltese financial cycle into low, medium and high risk regimes through the estimation of risk thresholds on two measures of cyclical risks. The Maltese economy was in the high risk regime from mid-2006 to 2008, and again from mid-2020 up to 2022, and by mid-2024 was in the medium risk regime. The risk thresholds we estimate allow policymakers to identify the build-up of risks ahead of time and conduct a pre-emptive assessment of any macroprudential policy intervention that is warranted, including a calibration of the appropriate policy tool.

**JEL Classification:** C11, C32, C34, C51, E44, E51, E58, G01

**Keywords:** Early warning system, risk thresholds, Threshold VAR, Markov-Switching model, macroprudential policy

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# 1 Introduction

Cross-country studies show that a third of credit booms have historically ended in a banking crisis (Dell’Ariccia et al., 2014). Although credit booms have a long economic history, their frequency has been observed to be rising since the 1980s in the wake of increasing financial liberalisation and deregulation (Dell’Ariccia et al., 2014). The study of financial crises is interesting and highly policy relevant in view of two stylised facts. First, a well-established finding in the literature is that financial crises are predictable outcomes of rapid credit and asset price booms (Minsky, 1977; Kindleberger, 1978; Borio and Lowe, 2002; Schularick and Taylor, 2012). In fact, Greenwood et al. (2022) show *ex-post* that the US economy had faced a 31% probability of entering a crisis way back in 2002 – well ahead of the Great Financial Crisis of 2008 – which continued to rise to 51% by 2006. Second, financial crises tend to have negative and long-lasting effects on GDP over the medium term (Cecchetti et al., 2009; Reinhart and Rogoff, 2009; López-Salido et al., 2017; Mian et al., 2020; Adrian et al., 2019). This emphasizes the important role of macroprudential policy in stabilizing the financial cycle to avoid these consequences.

From the 1970s through the early 1990s, Malta’s housing sector was characterised by substantial public sector intervention. The subsequent withdrawal of this intervention, coupled with the liberalisation of the financial sector in 1994, likely contributed to a 784% increase in total outstanding loans, and a 10,342% increase in outstanding mortgages, by 2023. These significantly outstripped growth in nominal GDP over the same period of 650%. House prices have also increased notably by 407% over the same period, growing more than four times faster than the Retail Price Index.<sup>1</sup> Yet, the Maltese economy has not experienced a systemic banking crisis since, and its banking system emerged relatively unscathed from the Great Financial Crisis despite the observed correction in property prices which followed (see Figure 1).<sup>2</sup> While this is undoubtedly a favourable outcome which is partly attributable to prudent lending practices, it ironically has some ‘less desirable’ implications for developing policymaking tools and frameworks. In the absence of experience of crises it is hard to test the ability of early warning indicators to detect potential turning points, which may otherwise indicate impending distress in the financial system and the associated spillovers to the real economy.<sup>3</sup> At the same time, the absence of a crisis to date does not rule out potential crises in the future.

In this paper we leverage the stylised facts on financial crises to address this issue by developing an early warning system for Malta based on risk thresholds. We build on earlier work and use two summary indicators, the cyclical Systemic Risk Indicator (cSRI) (Vella, 2024) and the semi-structural credit gap (Gatt, 2024), to derive our benchmark results. The risk thresholds we estimate allow policymakers to identify the build-up of risks ahead of time and conduct a pre-emptive assessment of any macroprudential policy intervention that is warranted, including a calibration of the appropriate policy tool. We specify three risk regimes, which we denote as low, medium and high. To explain the significance of these regimes we refer to macrofinancial

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<sup>1</sup>See the Central Bank of Malta’s [Historical Annual Database](#), which holds time series data for several macroeconomic and financial data, some of which starting from the 1940s and 1950s.

<sup>2</sup>See the database within [Lo Duca et al. \(2017\)](#) for a cross-country list of crises dates.

<sup>3</sup>That is, one cannot outright state that based on past events, an increase in credit beyond a certain magnitude over a 3-year horizon is clear indication of an impending crisis.

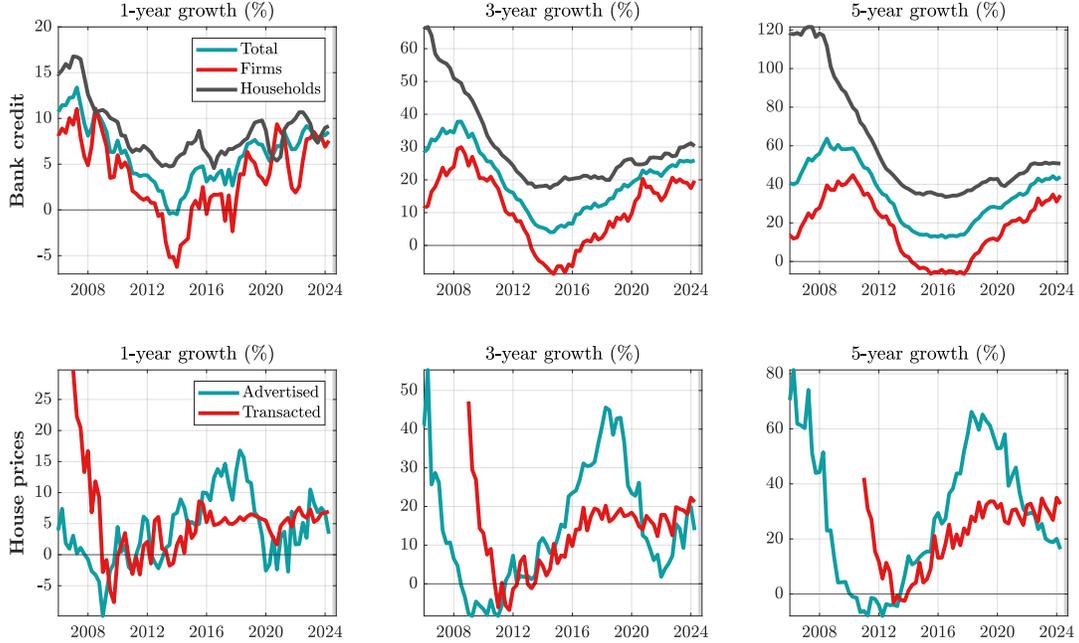


Figure 1: Credit and house price growth in Malta

Notes: The top row shows growth in bank credit across different horizons, while the bottom row shows growth in two measures of house prices, based on advertised and transacted prices, over the same horizons. Data for transacted house prices is only available from 2006 onwards. Total credit is the sum of household and firm credit. All variables are in nominal terms. See Appendix A for data sources and more details.

models with occasionally-binding constraints, such as those found in [Kiyotaki and Moore \(1997\)](#) and [Guerrieri and Iacoviello \(2017\)](#). A financial friction derived from information asymmetries between the lender and the borrower gives rise to a borrowing constraint which depends on the value of an underlying asset. In these microfounded models, slack financing constraints can start to bind in the wake of shocks, separating the space of actions for households, firms and governments into two states, constrained and unconstrained. The risk regimes we refer to correspond to different stages of the financial cycle in which an economy moves from the unconstrained to the constrained state.<sup>4</sup>

The low risk regime reflects periods in which asset prices are low and stable, and credit growth and leverage are low. Although households and firms can hold their wealth in a variety of assets, the key asset we have in mind in this paper is real estate, and with a slight abuse of terminology we use the term house prices in our discussion.<sup>5</sup> Whether borrowing constraints are binding or not in the low risk regime depends on the expected path of house prices. If the latter are expected to rise then constraints can be slack, despite current low asset prices. Nevertheless, credit growth can be weak or negative in this regime, and low leverage is the key contributor to

<sup>4</sup>See [Claessens and Kose \(2014\)](#) for a non-technical survey of the literature on financial crises. The classical references are [Minsky \(1977\)](#) and [Kindleberger \(1978\)](#).

<sup>5</sup>The same arguments hold for commercial real estate, although the absence of a commercial real estate indicator for Malta does not allow us to run the same analysis as we do using house prices.

low risk. The medium risk regime captures the transitory ‘build up’ phase in which credit and house prices start rising, possibly stimulated by optimism and positive sentiment that lead to perceived investment opportunities. Positive expectations about the future path of house prices keep borrowing constraints slack, as lenders assess a low probability of default or full recovery of their exposures in the case of default, via the repossession of an asset which is appreciating.

As house prices and credit keep on rising the economy transitions to the high risk regime. Real estate prices become misaligned from fundamentals, and debt levels are considered ‘excessive’. The sustainability of the growth in house prices and credit starts to be questioned, as does the resilience of borrowers and lenders to shocks. In the absence of shocks the system self-corrects as excessive demand pressures on credit and house prices subside through fading optimism. Over time credit and house prices re-align with fundamentals through further economic growth, without any economic fallout. In this case, high risk equates to high macro-financial stress but not to a crisis, and the economy transitions back to the medium and then the low risk states. On the other hand, a sudden slow-down driven by negative sentiment or an external shock can cause some households and firms to start to deleverage and rebalance their portfolios, exerting downward pressure on asset prices and on economic activity. At this point borrowing constraints become binding and can have a contractionary effect on the real economy through reduced credit supply and expenditure.<sup>6</sup> If this process is left unchecked it can potentially set off a cascade of fire-sales and default, with implications for banks’ profitability and their balance sheets, depending on the level of capital buffers in place. This leads to a deep economic contraction which can have long lasting effects on output, as discussed above. Table 1 summarizes the narrative under each regime.

Table 1: The financial cycle and risk regimes

<b>Risk Level</b>	<b>Asset Prices</b>	<b>Credit Growth</b>
<b>Low</b>	Low and stable	Weak or negative
<b>Medium</b>	Start to rise driven by optimism and perceived investment opportunities	Follows on the back of rising collateral values
<b>High</b>	Keep on rising, affordability and sustainability questioned	High but lenders wary, borrowers vulnerable to sudden slow-down, shocks can lead to deleveraging, portfolio rebalancing, binding constraints, potential fire-sales, and so on.

In our benchmark three regime approach we find that the Maltese economy was in the high-risk regime in two instances over the past two decades; from mid-2006 to the end of 2008, during a time of exuberance related to Malta’s accession to the EU in 2004 and euro adoption in 2008,

<sup>6</sup>See [Gatt \(2023\)](#) for an analysis of how macroprudential policy can be used to limit the extent to which binding financial constraints lead to deep economic contractions following a housing bubble.

and then again around the onset of the COVID-19 pandemic (mid-2020) up to the end of 2022.<sup>7</sup> The Maltese economy is judged to have been in the medium risk regime by 2024. The second approach we use, which adopts a binary ‘low–high’ risk classification, also delivers two main instances of high risk episodes, with similar timings. This model, which assigns probabilities to the risk states, indicates a rising probability of being in the high risk regime towards mid-2024. As already stated, neither of the two high risk instances precipitated a crisis. We characterise these *ex-post* as having been periods of ‘high stress’, during which the economy was likely more vulnerable to a financial crisis if it were hit by a large and unfavourable shock.

The use of an early warning system should consider the potential for false positives and false negatives, together with the trade-off between conservative action due to risk aversion, and policy paralysis due to real-time indicator uncertainty. Greenwood *et al.* (2022) show that their indicator, informed by data from several countries, still generates false alarms (false positives), as less than half of high risk episodes originating from developments in either corporate or household credit were followed by a crisis. On the other hand, several actual crises in their sample were not preceded by the high risk signal (false negative). This illustrates the trade-off inherent in any such threshold, including those we estimate in this paper. A low tolerance for switching to the high risk regime captures many crises but also issues many false alarms, which can lead to unwarranted policy actions and the associated drag on activity, but a high tolerance may miss the tell-tale signs of the build-up of risks. Nevertheless, an important policy consideration is that any early warning framework which anticipates risks even a year ahead may still not give sufficient lead time for the appropriate macroprudential measures to be decided upon and implemented.<sup>8</sup>

The rest of this paper is structured as follows. In Section 2 we explain the methodology we adopt in this paper and link it to the literature on non-linearities as applied for detecting periods of high financial stress, or for state-dependent transmission of monetary policy. Section 3 presents the results from our model estimations and comments on them, while Section 4 extends the set of indicators on which the models are estimated and compares the timing and signalling properties of these indicators jointly in a heatmap.

## 2 Thresholds via non-linear models

Traditional early warning models for analysing financial stress phases can be categorised into several approaches. One approach is the signalling method, where each indicator is modeled individually, primarily in a univariate setting (Kaminsky *et al.*, 1998). Another approach is the discrete choice method, which transforms indicators into crisis probabilities using probit or logit models (Bussiere and Fratzscher, 2006). Additionally, a decision tree approach employs numerical algorithms to allocate variable sets with significant discriminatory power into a decision tree

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<sup>7</sup>The first instance extends up to 2012Q3 when based on the credit gap, due to developments in the commercial credit market which keep the overall credit gap elevated prior to a deleveraging phase in the mid-2010s.

<sup>8</sup>For instance, the Capital Requirements Directive (CRD) requires national authorities to announce increases to the Countercyclical Capital Buffer (CCyB) rate with up to a year’s notice, unless exceptional circumstances justify a shorter notice period.

format (Frankel and Wei, 2004). We follow the first two approaches, through the estimation of a Threshold VAR model and a two-state Markov-Switching model with time-varying probabilities.

## 2.1 A Threshold VAR

Although most empirical applications use VAR models in their linear form, there are a number of extensions which can be used to study non-linearities. The Threshold VAR (TVAR) offers one such approach and has several appealing features. Firstly, it provides a straightforward way to account for potential non-linearities, such as asymmetric responses to shocks or the presence of multiple equilibria. Additionally, it uses one of the endogenous variables as the basis for signalling different regimes. Consequently, any switches between regimes in the model can be abrupt and are solely determined by the dynamics of this variable (Afonso et al., 2018). This model has been used with success to capture asymmetries and characterise the point at which they arise.

Alessandri and Mumtaz (2017) analyse the predictive power of financial market indicators for the US economy using a VAR model with stochastic volatility and a threshold VAR (TVAR) model. They show that these non-linear versions of the model would have improved forecasting performance during the period 1983-2012 relative to a standard VAR model with the same information set. They also show that the inclusion of financial variables would have been able to indicate a rising probability of a recession in early 2008 much more strongly when coupled with the non-linear VARs. This is due to the structural break that results from financial crises, which a linear VAR would miss.

Afonso et al. (2018) also employ a TVAR in which the indicator variable is the Financial Stress Index, and show that during high financial stress periods a financial shock causes output in the US, UK, Germany and Italy to contract by more than if the shock hits during a low stress period. More recently, De Santis and Tornese (2024) use a Bayesian TVAR, Bayesian Smooth Transition VAR and non-linear local projection models to detect non-linearities in the propagation of monetary policy shocks in the US. They demonstrate that monetary policy shocks have greater influence in the low growth environment, resulting in a negative impact on output and goods prices. Conversely, in the high growth environment, the effect on goods prices is less pronounced. These results are in line with earlier findings of Balke (2000) and Li and St-Amant (2010), who find differential effects of monetary policy across financial regimes.

Duprey et al. (2017) produce a monthly Country-Level Index of Financial Stress (CLIFS) to capture financial cycles dating systemic financial stress periods for 27 EU countries. The benchmark CLIFS captures data from three financial market segments; the equity market, the bond market and the foreign exchange market. Three versions of the CLIFS measure are constructed; the benchmark CLIFS, an extension with banking sector stress and another extension with housing sector stress. The authors employ a TVAR model to identify periods of systemic financial stress by conditioning on instances where financial market stress rises above an estimated critical threshold. In the case of Malta, the model identifies heightened systemic financial stress between January 2001 and July 2003, and between November 2011 and September 2012. During the initial high-stress period (2001—2003), the Maltese capital market was still in its infancy. Given the market’s limited depth both at the time and even in more

recent years, the index was and remains quite volatile. In fact, the Malta Stock Exchange equity price index tripled in value between December 1998 and January 2000, only to lose half its value by December 2002 – before recovering most of it over the following two years. These dynamics likely underpinned the initial period of elevated stress, and perhaps other periods too.

We contribute to this literature by using a TVAR model to establish suitable risk cut-offs which associate existing cyclical risk indicators with different risk regimes. We extend the framework used in [Alessandri and Mumtaz \(2017\)](#) to allow for three possible regimes, which we label as low (L), medium (M) and high (H) risk environments. The TVAR model is defined as:

$$Y_t = c(r_i) + \sum_{j=1}^J \beta_j(r_i) Y_{t-j} + v_t, \quad v_t \sim N(0, \Sigma(r_i)) \quad (1)$$

where  $Y_t$  is a vector of  $N$  endogenous variables and the VAR parameters  $\beta$  and residual covariance matrix  $\Sigma$  are a function of regime  $r_i$ ,  $i \in \{L, M, H\}$ . This is our benchmark model given that we are able to characterise three regimes through the use of a prior belief on the thresholds. We set the lag length  $J$  at four since we use quarterly data. The  $d^{\text{th}}$  lag of one of the endogenous variables  $z_t \in Y_t$  is used to identify the thresholds, such that the state is predetermined. The regimes are then defined as:

$$r_i = \begin{cases} r_L & \text{if } z_{t-d} \geq Z_1^* \\ r_M & \text{if } Z_1^* < z_{t-d} \leq Z_2^* \\ r_H & \text{otherwise,} \end{cases} \quad (2)$$

where we suppress the dependence of  $r$  on  $z$  to simplify the notation. The thresholds  $Z_1^*$  and  $Z_2^*$  belong to the set of unknown parameters which we estimate.

The vector  $Y_t$  consists of Maltese real GDP growth in Malta, Maltese Harmonised Index of Consumer Prices (HICP) inflation, euro area real GDP growth, euro area HICP inflation, the Shadow Short Rate (SSR) ([Krippner, 2013](#)) as a proxy for euro area monetary policy, and a proxy for cyclical systemic risks.<sup>9</sup> We estimate two versions of this model with alternate measures of cyclical risks. The first measure is the cyclical Systemic Risk Indicator (cSRI), defined as the first Principal Component of four macro-financial variables ([Vella, 2024](#)). The data sample used for estimation spans the period 2006Q1 to 2024Q2 for this version, since the cSRI is only available from 2006Q1. The second measure is the semi-structural credit gap for the private sector, derived from a multivariate filter ([Gatt, 2024](#)). The model which uses this risk variable includes data from 2001Q1 up to 2024Q2. [Figure 2](#) plots the data we use in this paper.

The benefits of including a composite indicator like the cSRI into the model is that implicitly the behaviour of several variables are included in the information set and the VAR is effectively a (static) Factor Augmented VAR ([Alessandri and Mumtaz, 2017](#), p.68). We set the delay parameter  $d = 2$  when the indicator variable  $z_{t-d}$  is the cSRI, and  $d = 1$  when we use the credit gap, which delivered the most reasonable results. In both estimations we add a dummy

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<sup>9</sup>In our initial testing we also included other variables, such as a measure of bond spreads and the EU Composite Indicator of Systemic Stress (CISS), yet we obtained unsatisfactory results and convergence issues.

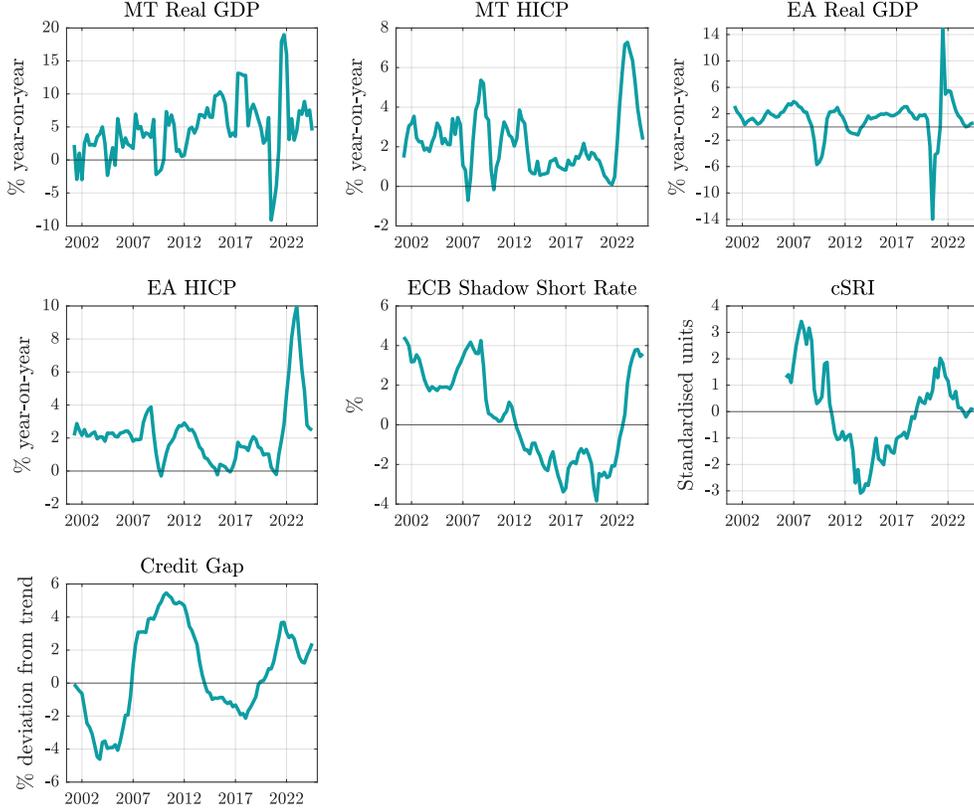


Figure 2: Macroeconomic data used in the models

Notes: MT and EA denote Malta and euro area, respectively. See Appendix A for data sources and transformations.

variable for the COVID-19 pandemic, which takes a value of 1 between 2020Q1 and 2020Q4, and -1 between 2021Q1 and 2021Q4. Given that we work with variables in growth rates, this dummy captures the initial drop in economic activity in the first year of the pandemic, and the subsequent correction which was spurred by a host of government policies, and a statistical base-effect.

We estimate the TVAR (1) via Bayesian methods, employing the natural conjugate prior for the VAR parameters (Sims and Zha, 1998) implemented using dummy observations as in Bańbura et al. (2010). Denoting regressors on the right hand side of (1) by  $X$ , we define these dummy observations as:

$$Y_D = \begin{pmatrix} \text{diag}(\delta_1 \sigma_1, \dots, \delta_N \sigma_N) \\ \kappa \\ \mathbf{0}_{N(P-1) \times N} \\ \dots \\ \text{diag}(\sigma_1, \dots, \sigma_N) \\ \dots \\ \mathbf{0}_{1 \times N} \end{pmatrix}, \quad X_D = \begin{pmatrix} \frac{J_P \otimes \text{diag}(\sigma_1, \dots, \sigma_N)}{\kappa} & \mathbf{0}_{NP \times 1} \\ \mathbf{0}_{N \times NP} & \mathbf{0}_{N \times 1} \\ \dots & \dots \\ \mathbf{0}_{1 \times NP} & \epsilon \end{pmatrix} \quad (3)$$

where  $\delta_i$ ,  $i = 1, \dots, N$  are the prior means on the coefficients of the first lag of variable  $i$ ,  $\sigma_i$  are scaling factors,  $\kappa$  is a hyperparameter which controls the overall tightness of these priors,  $J_P = \text{diag}(1, \dots, P)$  and  $\epsilon$  controls the tightness of the prior on the constant. The matrix  $X_D$  denotes regressors on the right hand side of (1). We follow Bańbura et al. (2010) and set  $\delta_i$  to zero since all the variables in the model are stationary, and set the scaling factors  $\sigma_i$  equal to the variance of residuals from a univariate regression on each time series.<sup>10</sup> We set  $\epsilon = 10^{-5}$  which translates to a flat prior on the constants, as is customary. A relatively loose overall tightness on the VAR parameters is also used. The hyperparameter  $\kappa$  is set to 1 when the credit gap is used as the indicator variable, and a slightly tighter value of 0.6 for the TVAR featuring the cSRI is used, since the time series available for estimation is shorter in this case. The augmented data series  $Y^* = [Y; Y_D]$  and  $X^* = [X; X_D]$  are then used in the estimation.

Importantly, the same priors for the VAR parameters across all regimes are used. As discussed in Alessandri et al. (2022), this may be counterintuitive since the behaviour of the variables is likely conditional on the regime that the economy is in, but by imposing the same prior we do not force this behaviour *ex-ante* but allow it to be revealed by the data, if present. The priors for the VAR parameters admit a known form for the posterior distributions, and we use a Gibbs sampler to construct these posterior distributions given their known moments. Turning to the thresholds  $Z_1^*$  and  $Z_2^*$ , we assume a normal prior centred around the 25<sup>th</sup> and 75<sup>th</sup> percentile of the indicator variable, respectively

$$Z_1^*, Z_2^* \sim N(\mu, \sigma_Z^2 I) \quad (4)$$

with  $\mu = [\mu_{0.25}, \mu_{0.75}]$  and  $\sigma_Z^2$  scaled at 0.015 and 0.10 when using the cSRI and the credit gap, respectively.<sup>11</sup>

We use the random-walk Metropolis-Hastings algorithm to sample the posterior distributions of the thresholds for a given Gibbs draw of the VAR parameters. In our application the algorithm endogenously fine-tunes the variance of the proposal distribution in the Metropolis-Hastings step based on the average acceptance rate over the previous 500 draws, such that this rate fluctuates within 20-35%. This ensures that the sampler explores the entire space around the posterior distributions of interest. We estimate the TVAR models using 100,000 iterations of the Metropolis-within-Gibbs sampler and retain the last 40,000 draws. Given the inherently high autocorrelation within the draws for the thresholds, we apply a thinning procedure which retains every fifth draw, such that all the posterior distributions are approximated with 8,000 draws. More details on the estimation diagnostics are shown in Appendix B.

## 2.2 A Markov-Switching model

Our second non-linear application is a Markov-Switching model with time-varying transition probabilities. The onset of a crisis or high stress period can be sudden, and this non-linear model

<sup>10</sup>The short time series does not allow us to split the data into a training sample and an estimation sample.

<sup>11</sup>These values imply a 95% probability density which spans the 17–40 and 65–82 percentiles for the lower and upper thresholds, respectively, for the version of the model with the credit gap, and 22–36 and 71–79 percentiles for the version which uses the cSRI. We comment on the sensitivity of the results to different priors in Section 3.

caters for these abrupt changes in economic relationships (Kim and Nelson, 1999), making it ideal for the study of risk regimes. The departure from fixed transition probabilities makes the estimation of the model more involved, but as shown in Diebold et al. (1994), not including this information can lead to poor and untimely estimates of regime switches. Using a Markov-Switching VAR model, Hartmann et al. (2015) show that the response of an economy to shocks differs across periods of high and low systemic stress. Furthermore, Duprey and Klaus (2017) show how a Markov-Switching model consistently outperforms a standard binary early warning model in predicting financial stress up to three quarters in advance, across a wide range of model specifications. The Markov-Switching framework has also been used in other areas of study. For instance, Amisano and Fagan (2013) use it to study low and high inflation regimes, providing evidence for the monetarist view that changes in the money supply provide early indicators of shifts in inflation patterns. Lopes and Nunes (2012) apply the model to study currency crises, showing that the interest rate differential across countries is an important determinant of the transition probabilities from a crisis to a non-crisis state. In addition to the TVAR model, Duprey et al. (2017) make use of a Markov-switching model and a Markov-switching vector autoregressive (MSVAR) model to identify simultaneous financial market and real economy stress. The episodes of high financial stress characterised by the Markov Switching model are narrowed down to those events that are linked with real economic stress using an algorithm. Whilst the Markov Switching model is univariate, the MSVAR model jointly determines real economic and financial market stress regimes. Any significant change in only one of the two dimensions, can cause the model to trigger a systemic stress event.

We estimate a two-state Markov-Switching model with time-varying transition probabilities on a multivariate model of GDP growth  $y_t$ , which is characterised by two regimes, high and low macro-financial risk.<sup>12</sup> The model we use is relatively simple and is given by

$$y_t = \mathbf{X}_t \beta_{S_t} + v_t, \quad v_t \sim N(0, \sigma_{S_t}^2) \quad (5)$$

$$\beta_{S_t} = \beta_0(1 - S_t) + \beta_1 S_t \quad (6)$$

$$\sigma_{S_t}^2 = \sigma_0^2(1 - S_t) + \sigma_1^2 S_t \quad (7)$$

where  $\mathbf{X}_t$  includes the first lag of real GDP growth for Malta, the first lag for the inflation differential between Malta and the euro area, euro area real GDP growth and the first lag of the Shadow Short Rate (SSR) for the ECB policy rate (Krippner, 2013). The model is essentially an AR(1) process for GDP growth supplemented with exogenous variables. As in Amisano and Fagan (2013), who use a simple AR(1) process for inflation, our aim is not to write a detailed model of GDP growth but to use this model to identify different regimes.<sup>13</sup> We add an intercept dummy to take into account the effect of COVID-19 on GDP growth. The unknown indicator variable  $S_t = \{0, 1\}$  is a Markov-Switching discrete process describing the risk regime, where

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<sup>12</sup>We do not extend the model to three regimes since these are unlikely to be successfully identified with a short data sample in this setting. Our application of the Markov-Switching model is meant to cross-check the key findings from the TVAR model, which is our benchmark model.

<sup>13</sup>In other words, our specification is sufficient to capture most of the variation in GDP growth. The lag structure we use delivered the most sensible and numerically stable estimates. See Appendix A for more details on the data.

$S_t = 1$  denotes the high risk regime. This process follows a first-order Markov chain with time-varying transition matrix  $\mathbf{P}_t$ :

$$\xi_{t|t-1} = \mathbf{P}_{t|t-1}\xi_{t-1|t-1} \quad (8)$$

$$\mathbf{P}_{t|t-1} = \begin{pmatrix} p_{00}(\Gamma_{t-1}) & p_{10}(\Gamma_{t-1}) \\ p_{01}(\Gamma_{t-1}) & p_{11}(\Gamma_{t-1}) \end{pmatrix} \quad (9)$$

where  $\xi_{t|t-1} = [\Pr(S_t = 0|I_{t-1}); \Pr(S_t = 1|I_{t-1})]$  is an  $2 \times 1$  vector of probabilities of being in  $S_t = \{0, 1\}$  given information as at  $t - 1$ ,  $p_{ij}$  denotes the probability of being in state  $j$  given that the system was in state  $i$  in the previous period ( $p_{ii} = 1 - p_{ji}$ ,  $\forall i \neq j$ ).<sup>14</sup> The vector  $\Gamma_{t-1}$  denotes a set of lagged regressors and our notation emphasises the dependence of the transition probabilities on these. A probit model is used to describe the evolution of the state variable  $S_t$  conditional on the value of an unobserved variable  $S_t^*$

$$\Pr(S_t = 0) = S_t^* < 0 \quad (10)$$

$$S_t^* = \gamma_0 + \lambda z_{t-1} + \gamma_1 S_{t-1} + u_t, \quad u_t \sim N(0, 1) \quad (11)$$

where  $z_{t-1}$  refers to either the lagged cSRI or the lagged credit gap, and  $\Gamma_{t-t} \in \{z_{t-1}, S_{t-1}\}$ . The parameter  $\lambda$  is a measure of the sensitivity with respect to  $z_{t-1}$ . By estimating a probit model for the latent state variable  $S_t^*$  we allow the transition probabilities to reflect developments in cyclical risks and account for potentially time-varying persistence in any of the two regimes.

The time-varying transition probabilities that form the matrix  $\mathbf{P}_{t|t-1}$  are calculated using the normal CDF

$$\begin{aligned} p_{00}(\Gamma_{t-1}) &= \Pr(S_t = 0|S_{t-1} = 0) \\ &= \Pr(u_t < -\gamma_0 - \lambda z_{t-1} - \gamma_1 S_{t-1}) \\ &= \Phi(-\gamma_0 - \lambda z_{t-1}). \end{aligned} \quad (12)$$

where  $\Phi(\cdot)$  is the Normal CDF. Similarly,  $p_{11}(\Gamma_{t-1})$  is given by

$$\begin{aligned} p_{11}(\Gamma_{t-1}) &= \Pr(S_t = 1|S_{t-1} = 1) \\ &= \Pr(u_t \geq -\gamma_0 - \lambda z_{t-1} - \gamma_1 S_{t-1}) \\ &= 1 - \Phi(-\gamma_0 - \lambda z_{t-1} - \gamma_1 S_{t-1}). \end{aligned} \quad (13)$$

The Markov Chain (8) is run for a given estimate of the time-varying regime probabilities, such that the evolution of  $\Pr(S_t = i)$  is guided by the determinants of the regime probabilities, which in our case are primarily the cyclical risk indicators.

We estimate the distributions of the parameters of the Markov-Switching model together with those of the latent binary indicator  $S_t$  and the continuous variable  $S_t^*$  using Gibbs sampling (Kim and Nelson, 1999). The indicator  $S_t$  is sampled conditional on all other parameter and state distributions using the Hamilton Filter, which in turn takes into account a time-varying

<sup>14</sup>Note that  $p_{01} = 1 - p_{00}$ . See Kim and Nelson (1999) for a textbook treatment of the model.

transition matrix.<sup>15</sup> The distribution for  $S_t^*$  is sampled using a left (right) zero-truncated normal distribution for when  $S_t = 0$  (1) with mean equal to the right-hand side of (11) and variance set to 1. Further details can be found in [Albert and Chib \(1993\)](#) and [Kim and Nelson \(1999\)](#). Markov-Switching models can be subject to the so-called label switching problem, since the likelihood is invariant to permutations in the labelling of the discrete states ([Geweke and Amisano, 2011](#)). It is therefore customary to impose an inequality constraint on one or a set of parameters (see, for instance, [Amisano and Fagan \(2013\)](#) and [Duprey et al. \(2017\)](#)). In this paper we associate the two regimes  $S_t = \{0, 1\}$  with low and high GDP volatility, respectively, and impose this constraint using rejection sampling

$$\sigma_0^2 < \sigma_1^2 \tag{14}$$

such that the high risk regime is identified by periods of high GDP volatility.

Table 2: Prior means for the Probit model

	<b>cSRI</b>	<b>Credit Gap</b>
$\gamma_0$	0.3	-1
$\lambda$	0.8	0.9
$\gamma_1$	0.7	0.5

We use Normal priors for the coefficients of equation (5) centered around 0 with variance of 0.5 and assume parameter independence using a diagonal variance-covariance matrix. The prior for the residual is an Inverse-Gamma distribution with scale set to 0.1 and 1 degree of freedom. These uninformative priors reflect our loose ex-ante beliefs about the values of these coefficients. The priors of the parameters of the probit model are also normally distributed and uncorrelated, with means as shown in Table 2. These means embed our beliefs that the two risk indicators we use are informative about the risk regime which the economy is in at any point in time. As [Amisano and Fagan \(2013\)](#) argue, some parameters in the model are likely to be poorly identified due to the low number of transitions in the short sample period. This is the case in our estimations and we therefore enforce these beliefs relatively tightly by setting all the variances of the probit parameters to 0.025. We set a lower prior mean for  $\lambda$ , and a higher mean for  $\gamma_1$ , when using the cSRI as it is more volatile compared to the credit gap. The parameter  $\lambda$  is the most important for the dynamics of the time-varying transition probabilities. Finally, lower levels of  $\gamma_0$  lead to less persistent values for the transition matrix  $\mathbf{P}_t$ , and our choice of values of 0.3 for the case of the cSRI and -1 when using the credit gap allow for the probabilities to be more responsive to movements in the underlying risk indicator. Since the cSRI is more volatile than the credit gap, we put a more conservative (higher) value.

The model is estimated using 20,000 repetitions of the Gibbs sampler as a burn-in, after which a further 50,000 draws are retained for the parameters of the GDP equation, the probit model, the time-varying probabilities and the latent variable  $S_t^*$ . These draws are subject to rejection sampling described above, in which the variance of the residual in the GDP equation

<sup>15</sup>The smoothed estimate for  $S_t^*$  is obtained using a backward-recursion step in our code akin to the Carter-Kohn algorithm ([Carter and Kohn, 1994](#)).

is higher in the high risk regime. We also add a second sampling condition that the AR(1) parameter in equation (5) is less than one in both regimes, to ensure non-explosive behaviour in either regime.

### 3 Risk regimes

We first focus on the results based on the TVAR, as this model is our benchmark. Figures 3 and 4 show the distributions of the estimated thresholds based on the cSRI and the credit gap, respectively, on the left panel. The mean of the prior distribution for each threshold is also shown. The right panel displays the kernel densities of both prior and posterior distributions for the two thresholds. When the indicator is the cSRI, the posterior distributions are concentrated more tightly around a higher mean than the priors, for both the upper and lower thresholds. When using the credit gap, the posterior means are not much different from the prior means but their distributions are significantly concentrated around them. The data is therefore informative on these cut-offs, and the models we estimate clearly identify the low, medium and high GDP volatility regimes as discussed in equation (2). Table 3 summarizes key moments of the posterior distributions for the thresholds.

Although we estimate probability distributions for the risk thresholds, we henceforth focus on the mean of these distributions to classify the regimes. Figure 5 shows that both the cSRI and the credit gap breached the high risk threshold in the mid-2000s, and then again in the early 2020s on the onset of the pandemic. This is somewhat consistent with the second episode of high stress identified by Duprey et al. (2017) for Malta for the period 2011–2012, although we note that the CLIFS indicator rises with a lag relative to either the cSRI or the credit gap, explaining this delayed timing of the high risk regime. Both indicators signal a transition to medium and low risk regimes in the mid-2010s, although the credit gap remains in the red zone for several years before declining. This is partly due to developments in credit to non-financial corporations, which started a gradual deleveraging process away from bank credit to other sources of finance, causing the estimated trend component to fall and generate a persistently positive credit gap for firms.

Table 3: Summary statistics for the TVAR risk thresholds

	10%	Mean	90%
<b>cSRI</b>			
Upper threshold	1.34	1.36	1.40
Lower threshold	-0.63	-0.46	-0.30
<b>Credit Gap</b>			
Upper threshold	2.91	2.99	3.05
Lower threshold	-1.32	-1.28	-1.25

Notes: The table shows the 10<sup>th</sup> and 90<sup>th</sup> percentiles, together with the mean of the posterior distributions of the estimated thresholds across the two indicators. ‘Upper’ and ‘lower’ thresholds denote the cut-offs between medium and high risk, and low to medium risk, respectively.

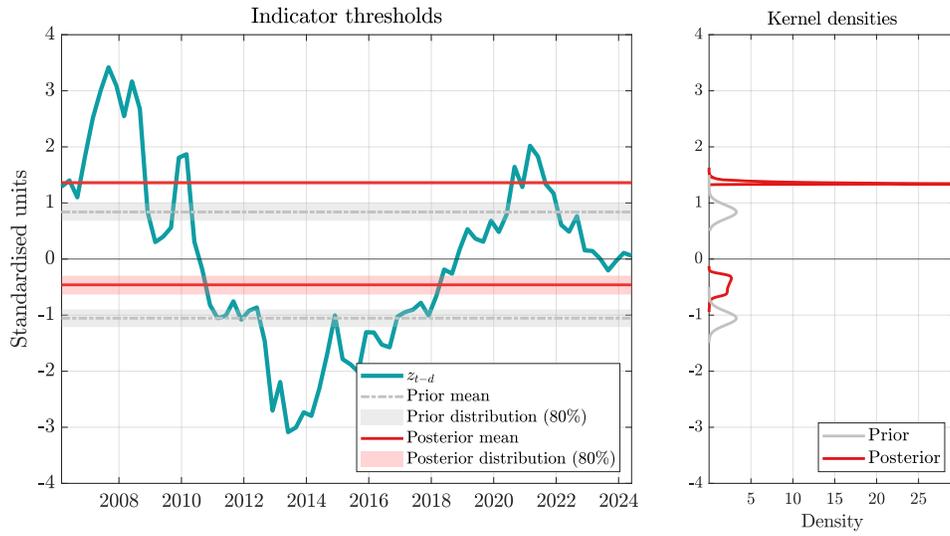


Figure 3: Estimated thresholds based on the cSRI

Notes: The figure shows the prior and posterior distributions of the thresholds as shaded areas in the left panel and as kernel densities in the right panel. Shaded areas correspond to the range covered by the 10<sup>th</sup> and the 90<sup>th</sup> percentiles of the distributions.

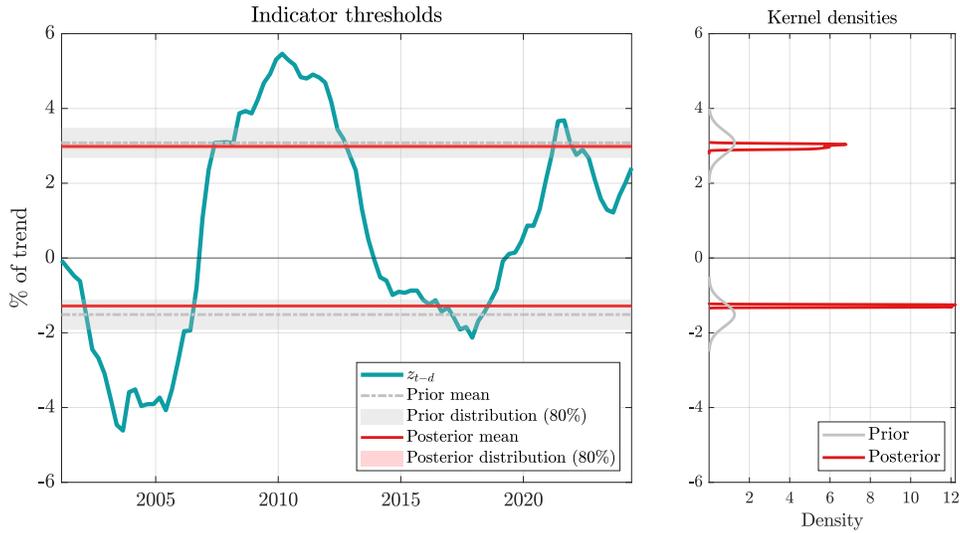


Figure 4: Estimated thresholds based on the credit gap

Notes: The figure shows the prior and posterior distributions of the thresholds as shaded areas in the left panel and as kernel densities in the right panel. Shaded areas correspond to the range covered by the 10<sup>th</sup> and the 90<sup>th</sup> percentiles of the distributions.

In the mid-2010s both indicators signal medium and low risks for several years, before indicating a switch to medium risk in mid-2018 and then a further transition to high risk in the early 2020s, coinciding with the onset of the COVID-19 pandemic. Once again, the cSRI transitions

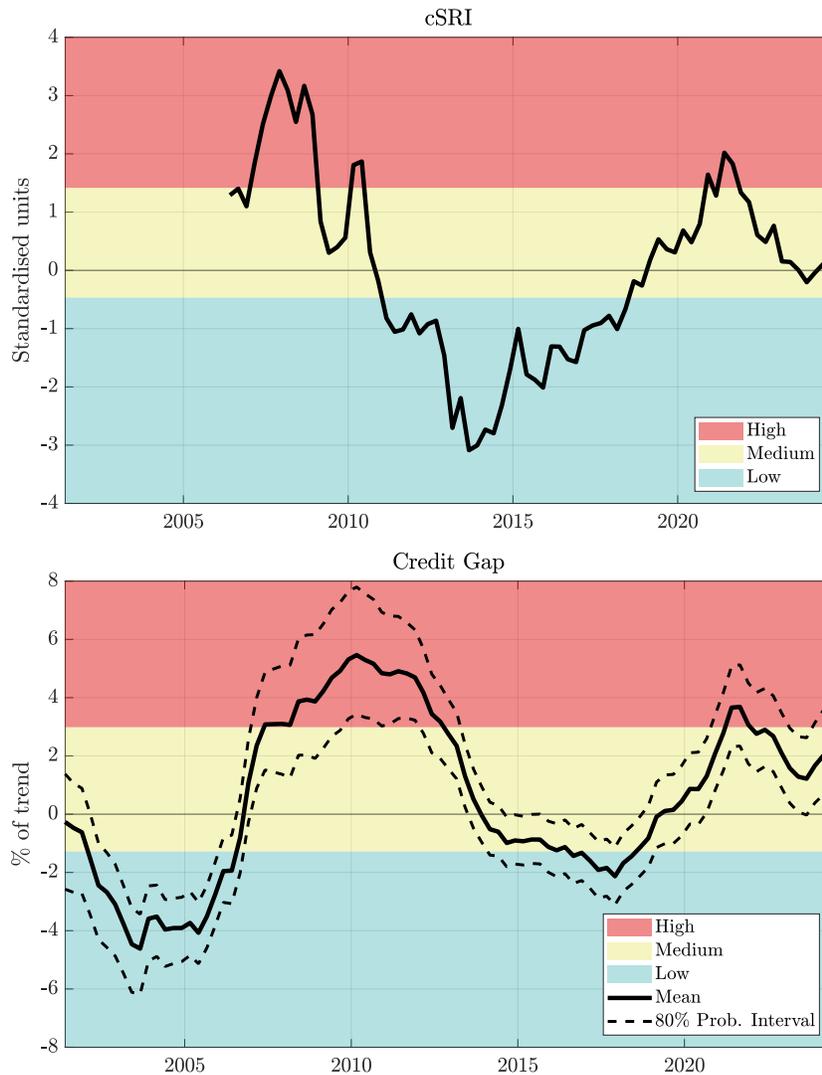


Figure 5: Risk regimes based on the TVAR

Notes: The figure shows the classification of the risk regimes based on the means of the posterior distributions of the upper and lower thresholds. The cSRI is available from 2006Q1 onwards. The 80% probability interval denotes the range between the 10<sup>th</sup> and 90<sup>th</sup> percentiles of the credit gap distribution.

to the high risk state some quarters before the credit gap. Towards the end of the sample both indicators transition to medium risk levels, although the credit gap shows a reversal and is rising again. It is important to note that the cSRI is affected by the high inflation that materialised during 2022 and 2023, since some of the components are expressed in real terms. We review the effect of this in Section 4 where we categorise risk regimes over an extended set of risk indicators. Furthermore, we note that the cSRI is a statistical measure of the financial cycle which is based on standardised variables. This indicator may therefore be vulnerable to moments estimated

over short time series. One of the variables in the cSRI is the house price-to-income ratio, which was very high and peaked in 2006, such that it biases the mean of this time series upwards. Consequently, deviations around this mean are sensitive to this high historical episode. The same pattern applies for the change in the debt service-to-income ratio. Towards the end of the sample both of these sub-indicators remained at moderate levels but below their (biased) long term average, leading them to contribute to declines in the cSRI. This further explains the apparent diverging trends between these two aggregate indicators. Nevertheless, the credit sub-components that feature in the cSRI all contribute positively, in line with the signal derived from the credit gap.

In the case of the credit gap we also show the space spanned by the 10<sup>th</sup> and 90<sup>th</sup> percentiles of its distribution, to better convey the uncertainty around the classification of risks. From a policy perspective this allows for a probabilistic assessment of a transition from one risk regime to another based on the area under the density that falls under a regime of interest.

To assess the importance of our choice of prior on the results, we re-estimate the model after centering the lower and upper threshold priors on the 40<sup>th</sup> and 60<sup>th</sup> percentiles of the risk indicators, respectively. In the case of the credit gap, while the posterior mean of the lower threshold is virtually unchanged, the posterior mean of the upper threshold falls slightly from around 3.0% to 2.1%. This translates to a slightly earlier transition to the high risk regime as the credit gap starts rising. In practical terms, this implies that the *mean* credit gap, which stands at 2.4% at the end of the sample, lies in the high risk regime with this alternative prior.<sup>16</sup> In the case of the cSRI the upper threshold posterior mean also falls from 1.36 to 0.81, although this remains higher than the prior mean, indicating that values higher than the 60<sup>th</sup> percentile of the cSRI are consistent with a transition to a high risk regime. This robustness check shows that the estimated thresholds are to some extent influenced by the priors, but the data remains informative as the posterior never overlaps the prior. The choice of the 25<sup>th</sup> and 75<sup>th</sup> percentiles for the lower and upper prior thresholds is conservative as it aims to avoid the potential for frequent ‘false positives’ for the classification of high risk periods, while remaining reasonably robust to changes in cyclical risks. This approach ensures that the model’s risk classifications are both reliable and practical for policy-making purposes.

We do not calculate non-linear impulse response functions to a financial shock for two reasons. First, we lack a clear identification strategy that defines this shock in the context of different regimes, since the same shock can have different effects on the endogenous variables. This potentially rules out magnitude and sign identification schemes. Although a recursive identification strategy is feasible, it is well-known that in general this lacks a precise interpretation of the shock and in our testing we found that results can be sensitive to the ordering of the variables. Second, although it would be interesting to study the reaction of the economy to shocks in different regimes, this is outside the primary scope of this paper. Therefore we do not pursue this further here and we leave this for future work.

Next we cross-check our results with those obtained using the two-state Markov-Switching model with time-varying probabilities. We restrict the attention to the probability of being in

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<sup>16</sup>We are unable to estimate the model with prior thresholds which are closer to the tails of each indicator, such as at the 20<sup>th</sup> and 80<sup>th</sup> percentiles, as this would result in too few observations for estimating the VARs in the low and high risk regimes.

the high risk state ( $\Pr(S_t = 1)$ ) and the characterisation of risk regimes over time. We provide a summary of the main estimation results for the GDP equation and the probit model and present the full estimation results in Appendix B. The parameters of the GDP equation differ across the two states, with the low risk state governed by high persistence in GDP growth, and GDP growth responding negatively to the EA-MT inflation differential, and the proxy for the ECB monetary policy rate, and weak to no sensitivity to EA GDP developments. The high risk state in turn attributes less persistence in GDP growth and a stronger role for economic activity in the euro area. This may suggest that the high risk regime is capturing periods in which some relationships may not hold, as GDP growth is dominated by shocks, which also drive euro area GDP growth, explaining the co-movement which we estimate.<sup>17</sup>

We show kernel density plots for the prior distributions and the estimated marginal posterior distributions in Figures B.8–B.9 in Appendix B. The posteriors largely overlap the priors, suggesting that the data is mostly uninformative about these parameters. Additionally, the models may be subject to some identification issues as the posterior for the coefficient  $\lambda$  that loads on the credit gap appears to be bimodal. This weak identification is likely to be the result of the short sample we have at our disposal, and highlights the usefulness of our Bayesian approach to obtain results. Given its importance in driving the results, we experiment with different values of the priors, notably for the parameter  $\lambda$ , to assess how sensitive the results are to different values. A looser prior or one centered around a lower mean leads to quick and volatile transitions in and out of the high risk regime, which is unlikely to capture relevant developments in the Maltese economy. Despite these tight priors, the probability of being in the high risk regime is still somewhat volatile at times when the underlying indicator is the cSRI, since the latter is also quite volatile.

Figure 6 shows the probability that the economy is in the high risk state for each of the two risk indicators used. We err on the side of caution and impose two conditions which must be satisfied to characterise a transition to the high risk regime. The first rule requires the probability  $\Pr(S_t = 1)$  to be *greater than 60%*, slightly higher than the 50% threshold typically used in other applications of the Markov-Switching model. The second is that this 60% threshold is breached *for at least two quarters*, as in De Santis and Tornese (2024). Through these conditions we reduce the potential for false or shortlived transitions, in line with the discussion on the trade-off between false positives and false negatives. This is especially valid in view of the fact that there is no banking crisis in the data used to estimate the model, raising our tolerance for a switch to the high risk regime.<sup>18</sup>

The resulting regimes are shown in Figure 7, where the areas shaded in red mark the high risk regime. The economy is characterised as being in the high risk state in the mid-2000s, with a duration that extends up to the mid-2010s based on the credit gap.<sup>19</sup> The lower panel once

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<sup>17</sup>Some of these parameters are estimated with uncertainty as the posterior distributions are wide and span both positive and negative values. A subset of these parameters also display bi-modality, which could indicate identification problems driven by the low number of observations available in each regime.

<sup>18</sup>This is an *in-sample* property, in the sense that there is no guarantee that this threshold remains appropriate for signalling the potential for a crisis if the economy is hit with unique shocks in the future.

<sup>19</sup>Although the cSRI is not available before 2006, we believe the probability of entering the high risk regime in the few years prior to this, had the cSRI been available, would have likely mirrored that we obtain using the

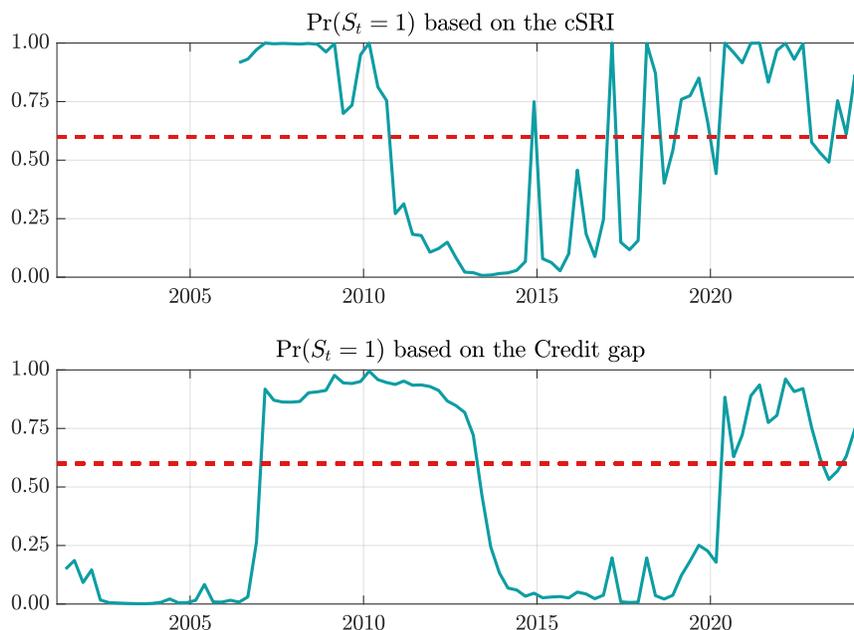


Figure 6: Probability of the high risk regime across indicators

Notes: The regime probability is the mean of the distribution of  $S_t$  over 50,000 Gibbs draws for the parameters of the Markov-Switching model. The threshold for a switch to the high risk regime is 0.6 (red dashed line).

again shows the distribution of the credit gap, even though the mean (solid black line) is used to estimate the model. The model assigns a high probability of being in the high risk environment again on the onset of the COVID-19 pandemic, and the probability subsides for a few quarters some years later only to rise again towards the end of the sample in mid-2024. The transition to the high risk state based on the cSRI once again occurs a few quarters before that obtained using the credit gap. These narratives align well with the findings based on the TVAR model, where the medium risk state in that model is split between the high and low risk regimes from the Markov-Switching model.

Note that unlike the results from the TVAR, the switch to the high risk state does not occur when the cSRI or the credit gap are always at a specific value. For instance, the switch in 2007 occurs when the mean credit gap is almost 2%, whereas it stands at less than 1% when the second switch occurs in 2020. This is due to the additional information available to the model besides the risk indicator itself, namely the dynamics of GDP growth, which informs the characterisation of risks. In fact, the sudden rise in risk in 2020Q2 coincides with the large contraction in GDP brought about by the pandemic, even though the credit gap was positive but stable. A second and related observation is that the probability of the high risk regime tends to rise very quickly, which we believe is a desirable property for an early warning system when used in conjunction with our classification rules listed above. Recall that the medium risk

credit gap.

regime of the TVAR is partly captured by either the low or high risk regime in the two-state Markov-Switching model, so the timing of the switch to the high risk regime from the latter may not always coincide with that of the high risk regime of the TVAR.<sup>20</sup>



Figure 7: Risk regimes based on the Markov-Switching model

Notes: The red shaded regions denote the high risk regime, based on a 60% probability threshold. The cSRI is available from 2006Q1 onwards. The 80% probability interval denotes the range between the 10<sup>th</sup> and 90<sup>th</sup> percentiles of the credit gap distribution.

We also estimate the models using two other potential proxies for the financial cycle as

<sup>20</sup>In an ideal scenario, we would have used half of the sample for an in-sample estimation and then conduct an *out-of-sample* evaluation on the remaining data. These results would then be compared to those obtained from the full in-sample estimation, to test the sensitivity of the results to the estimation period. However, given the limited number of observations and few full financial cycles in our data series, this option is not viable. This exercise would lack enough degrees of freedom and would be prone to very weak identification of differences between the different risk regimes.

a robustness check. We use the Central Bank of Malta’s Financial Conditions Index (FCI) (Borg and Micallef, 2018) and the CLIFS for Malta (Duprey et al., 2017). The FCI summarises co-movements in several financial variables, including bank and market interest rates, bank credit, deposits and profitability, non-performing loans, domestic and euro area equity prices, and the CISS measure of financial stress in the euro area. The CLIFS constructed for Malta aims to capture movements in equity, government bonds and foreign exchange, in addition to banking stress (if any). These sources of risk are likely of secondary importance relative to the domestic credit and housing related risks captured by the cSRI and the credit gaps, which are our benchmark indicators.

In the TVAR model, the CLIFS breaches the high risk threshold in the early 2000s, between 2010-2012, and again in the early 2020s after the onset of the pandemic. The high risk thresholds identified prior to 2020 are consistent with the model-based systemic financial stress episodes defined by Duprey et al. (2017) for Malta, mainly between January 2001 and July 2003, and between November 2011 and September 2012. The CLIFS signals a transition to medium and low risk regimes in the mid-2010s like the cSRI and the credit gap. Similar to the credit gap, the CLIFS stays in the high risk threshold for multiple years before declining and also breaches the high risk threshold during 2021 and 2022. These similarities with the credit gap are partly due to the developments in credit to non-financial corporations arising from non-bank credit sources of finance which are broadly captured in the CLIFS measure. Meanwhile, results based on the FCI are more consistent with our benchmark findings, such that the risk thresholds identify a shift to the high risk regime in the period 2006–2007 and 2019-2021, with another a brief transition which lasted for 3 quarters in 2015.

## 4 A risk heatmap

The results presented above focus on each indicator separately, and we note that both indicators tend to enter the high risk regime at around the same time. To better assess the coherence of transitions from one regime to another across indicators, as well as to understand sectoral developments within the credit gap, we apply a heatmap over an extended set of indicators. We estimate the risk thresholds for the cSRI based on nominal measures (see Vella (2024)), and the household and firm credit gaps (see Gatt (2024)).<sup>21</sup> We estimate the TVAR and the two-state Markov-Switching model for each of these additional indicators using the same methodology as used for the cSRI and the aggregate credit gap, respectively. This ensures that the thresholds relate to the dynamics of these specific risk measures.<sup>22</sup>

Figure 8 shows the regimes spanned by each indicator every quarter across the past two decades across our two models. As discussed above, we classify a transition from one state to another when each indicator breaches its specific risk thresholds for at least 2 consecutive quarters, as some noise in the indicators can signal a ‘false’ transition which is short-lived. The heatmaps show a consistent pattern across time, especially in the latter part of the sample.

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<sup>21</sup>The cSRI in nominal terms is appropriate towards the end of the sample, where inflation was significantly above its long run average, leading to a dampened cSRI which could understate risks.

<sup>22</sup>The results for each indicator are available in Appendix B.

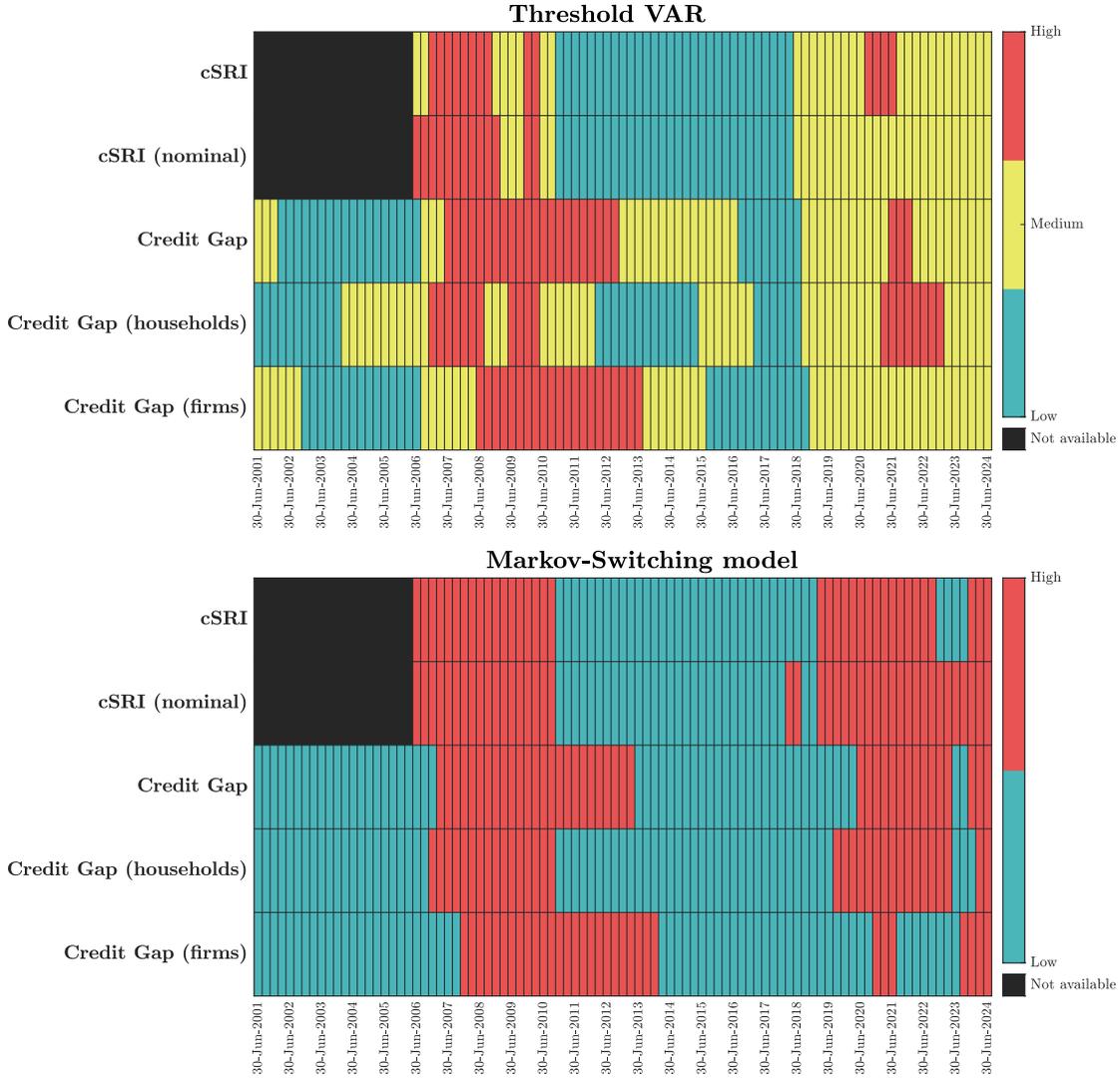


Figure 8: Heatmap of risk regimes across indicators

Notes: The figure shows the region spanned by each indicator at each point in time, with teal shading denoting an indicator which is below the low risk threshold, yellow shading denoting an indicator between the low and high threshold, and red shading indicating a breach of the high risk threshold. This classification is based on the posterior mean of the estimated thresholds from the TVAR estimated for each indicator.

When using the three regime TVAR we observe very similar transitions and timing from the low to medium risk, particularly in mid-2018, and in a subset of these, a high risk regime during the COVID-19 pandemic. The heatmap for the two-state Markov-Switching model similarly shows consistency in the flagging of risks across the set of indicators. It clearly flags two periods of broadly elevated stress (2007–2010 and 2019–2022) which correspond to the medium and high risk regimes identified using the TVAR. The probability of being in the high risk state rises again for all indicators towards the end of the sample, indicating a potential return to heightened risk-taking. This is in line with the developments both in the raw data shown in

Figure 1 and in the summary measures of risk used in our analysis. Towards the end of the sample credit and house prices continued to grow at a strong pace, and the cSRI (in nominal terms) and the credit gap remain positive and elevated.

It is interesting to note that the cSRI and the household credit gap signal very similar transitions across time, irrespective of which model we use. On the other hand, the credit gap for firms has a more unique identification of risks, which to an extent drives the ‘high’ risk classification of the aggregate credit gap during the period 2007–2012. These heatmaps are informative for the conduct of macroprudential policy because they can help identify the nature of cyclical risks insofar as characterising between sectoral and broad-based developments.

## 5 Conclusion

In this paper we characterise the state of macrofinancial risks over the financial cycle using a Threshold VAR, yielding estimates of risk thresholds over the space of low, medium and high risks. Our results are consistent across the two key risk indicators we consider, namely the cSRI and the aggregate credit gap. We also extend our results over a wider set of indicators and present transitions across regimes as an informative heatmap. To further assess the robustness of our results we also estimate a two-state Markov-Switching model for GDP growth regimes and yield similar qualitative results. The Maltese economy experienced two pronounced periods of elevated financial stress, the first during the Great Financial Crisis of 2007–2008, and the second during the COVID-19 pandemic. During the latter episode risks emanated specifically from the household sector, where residential real estate lending is the predominant driver of credit growth. Conversely, the early 2000s and mid-2010s were periods of low macrofinancial stress, particularly due to deleveraging efforts in the corporate sector.

We emphasise that these risk thresholds and regime identification provide a reasonable characterisation of the financial cycle but should not be considered as the sole factor that should weigh on decisions for any possible revision to any particular macroprudential policy stance. Any revisions to the latter are driven by a rich set of metrics, comprehensive system-wide and bank-specific stress tests, as well as expert judgement which makes use of soft data gathered from discussions with stakeholders. Furthermore, even anticipating risks a year in advance may still not provide sufficient lead time to determine and implement appropriate macroprudential measures. Nevertheless, the early warning system governed by these thresholds helps to formalise the macroprudential assessment further and assist the communication of any developments in risk to policymakers, stakeholders and the public.

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## Appendix A Data

The main sources of data used in this study are Eurostat (via DBnomics) and the Central Bank of Malta. Data codes for DBnomics, where relevant, are provided below.

### Household credit

Total credit to households for the period 2003Q4–2023Q2 is obtained from the Central Bank of Malta (OMFI loans to residents of Malta by economic activity) using end-of-period values. We fill in missing values for data prior to this period by obtaining corresponding series from the STREAM database, which is the Central Bank of Malta’s macroeconometric model, and splice the missing values for OMFI loans back to 2000Q1 based on quarterly growth rates.

### Firm credit

Total credit to firms for the period 2003Q4–2023Q2 is obtained from the Central Bank of Malta (OMFI loans to residents of Malta by economic activity) using end-of-period values, defined as total loans to the private sector less total household credit. We remove loans related to Special Purpose Entities and fill in missing values for data prior to this period by obtaining corresponding series from the STREAM database, which is the Central Bank of Malta’s macroeconometric model, and splice the missing values for OMFI loans back to 2000Q1 based on quarterly growth rates.

### House prices

Advertised house prices are sourced from the Central Bank of Malta’s house price index, which is based on advertised property prices. Transacted property prices are sourced from the National Statistics Office and are based on sale prices.

### GDP

Real GDP for Malta and the euro area are defined as the chain-linked 2015 volumes, and relate to the 2024Q2 data vintage and are subject to revisions.

- Malta real GDP: `Eurostat/namq_10_gdp/Q.CLV15_MNAC.NSA.B1GQ.MT`
- Euro area real GDP: `namq_10_gdp/Q.CLV15_MEUR.SCA.B1GQ.EA19`.

### HICP inflation

The HICP index is sourced from Eurostat and is transformed to quarterly averages and then into yearly changes.

- Malta HICP: `Eurostat/prc_hicp_midx/M.I15.CP00.MT`
- Euro area HICP: `Eurostat/prc_hicp_midx/M.I15.CP00.EA`.

## ECB policy rate

We use the Shadow Short Rate (Krippner, 2013, 2020) to proxy both conventional and unconventional ECB monetary policy. We obtain the monthly average series for the euro area from Leo Krippner’s website <https://www.ljkmfa.com/visitors/> and take quarterly averages.

## Indicators of cyclical risks

We use the cyclical Systemic Risk Indicator (cSRI) and the semi-structural credit gap as alternate measures of cyclical risks. The cSRI is constructed as the first Principal Component among the 2-year real bank credit growth, the house price to income ratio, the 1-year change in the economy-wide debt-service to income ratio, and the 2-year growth rate of total private sector debt; see Vella (2024) for more details. The semi-structural credit gap is obtained from a state-space model which decomposes observed credit into trend and cycle components. The model includes 11 observed variables, including GDP, inflation, unemployment, household and firm credit, household and firm lending interest rates, house prices, and euro area GDP, inflation and the policy rate. The equations that describe the evolution of the trend and cycles for any observable includes some terms from the other trends or cycles for other observables. The parameters of the model are estimated using Bayesian methods. The credit gap used in this study is a weighted average of the household and firm credit gaps, using outstanding shares as weights. See Gatt (2024) for more details.

# Appendix B Technical details and results

## B.1 Threshold VAR

### B.1.1 Estimation diagnostics

Figures B.1–B.2 below show the dynamic jumping distribution scale – the variance of the proposal distribution for the thresholds– which adjusts endogenously to keep the acceptance rate between 20% and 35%. It also shows the realised acceptance rate over the full sample and over the previous 500 draws, for the three versions of the TVAR models presented in the main text.

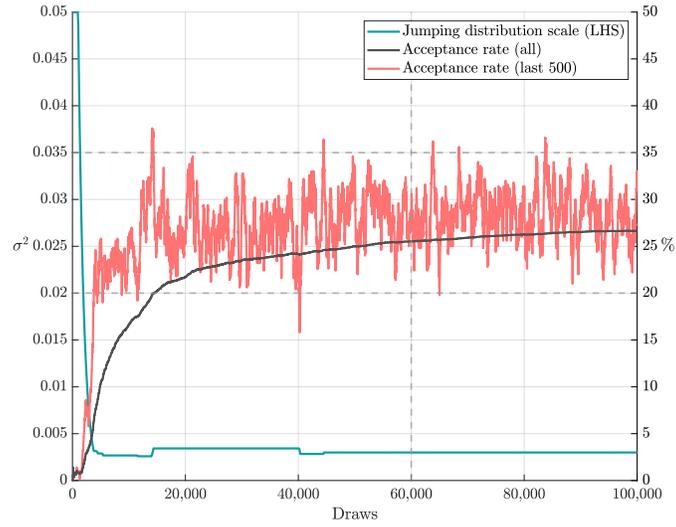


Figure B.1: Acceptance rate for the Metropolis-Hastings algorithm (cSRI)

Notes: The grey dashed vertical line denotes the cut-off between the burn-in sample and the retained draws, while the horizontal dashed lines in grey denote the ideal range for the acceptance rate.

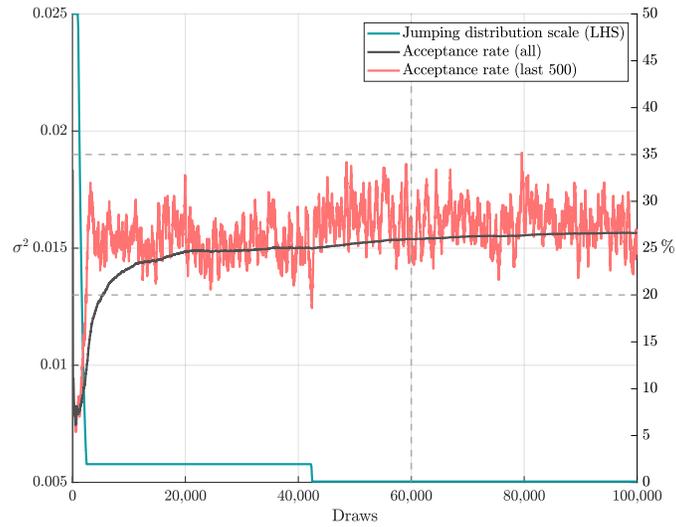


Figure B.2: Acceptance rate for the Metropolis-Hastings algorithm (Credit Gap)

Notes: The grey dashed vertical line denotes the cut-off between the burn-in sample and the retained draws, while the horizontal dashed lines in grey denote the ideal range for the acceptance rate.

### B.1.2 Extended set of results

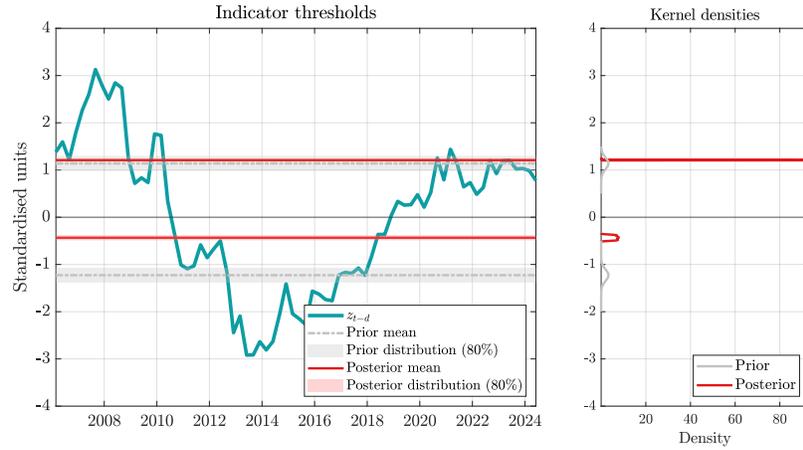


Figure B.3: Estimated thresholds based on the nominal cSRI

Notes: The figure shows the prior and posterior distributions of the thresholds as shaded areas in the left panel and as kernel densities in the right panel. Shaded areas correspond to the range covered by the 10<sup>th</sup> and the 90<sup>th</sup> percentiles of the distributions.

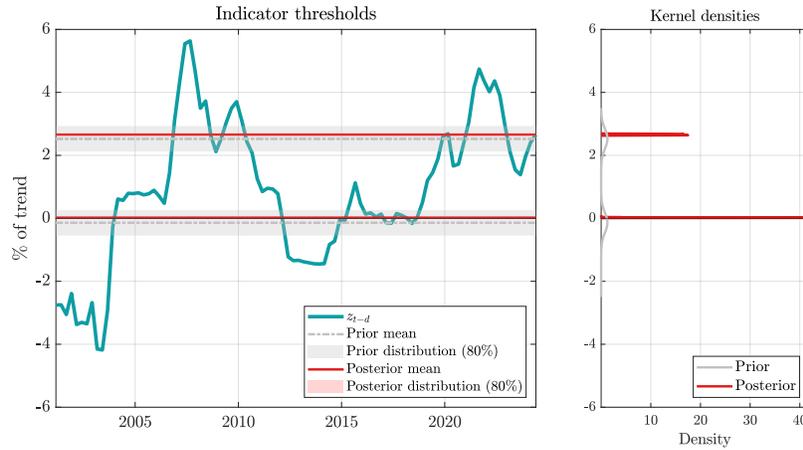


Figure B.4: Estimated thresholds based on the household credit gap

Notes: The figure shows the prior and posterior distributions of the thresholds as shaded areas in the left panel and as kernel densities in the right panel. Shaded areas correspond to the range covered by the 10<sup>th</sup> and the 90<sup>th</sup> percentiles of the distributions.

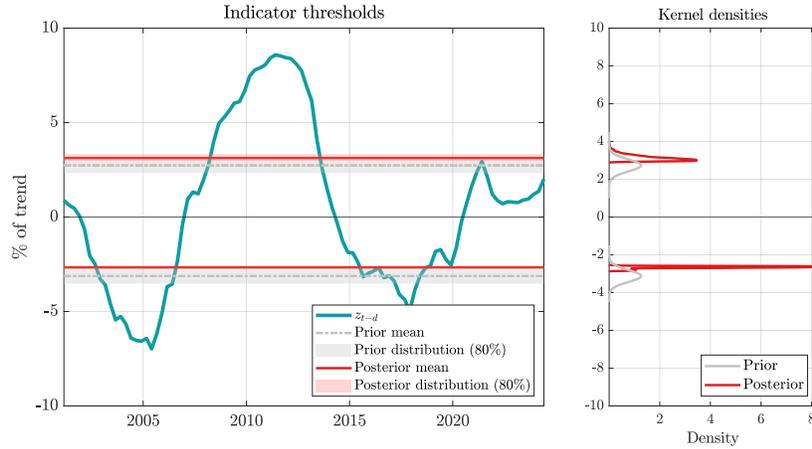


Figure B.5: Estimated thresholds based on the firm credit gap

Notes: The figure shows the prior and posterior distributions of the thresholds as shaded areas in the left panel and as kernel densities in the right panel. Shaded areas correspond to the range covered by the 10<sup>th</sup> and the 90<sup>th</sup> percentiles of the distributions.

## B.2 Markov-Switching model

### B.2.1 Estimation diagnostics

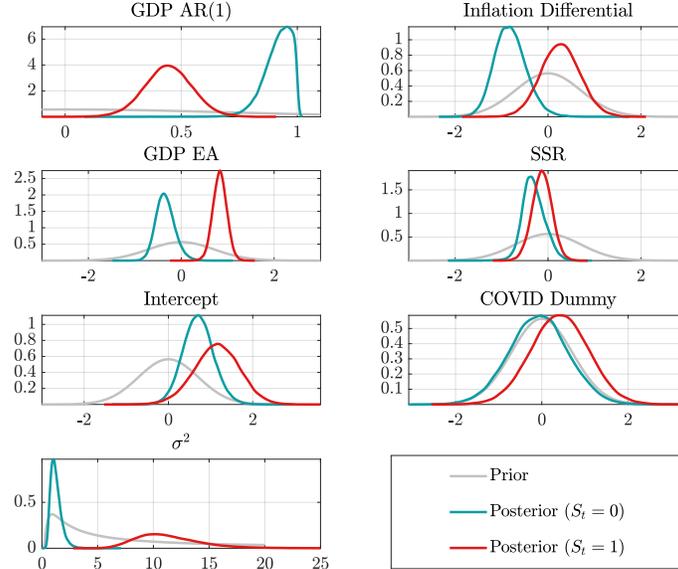


Figure B.6: Prior and posterior distributions for the Markov-Switching GDP equation based on the cSRI

Notes: The figure shows the prior and posterior distribution of the parameters in the GDP equation, corresponding to the low ( $S_t = 0$ ) and high ( $S_t = 1$ ) risk regimes. The kernel densities are based on the 50,000 retained draws from the Gibbs sampler.

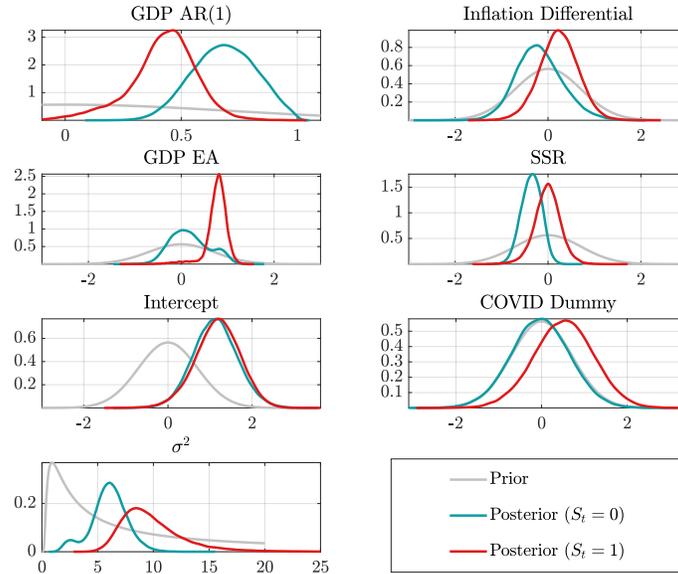


Figure B.7: Prior and posterior distributions for the Markov-Switching GDP equation based on the credit gap

Notes: The figure shows the prior and posterior distribution of the parameters in the GDP equation, corresponding to the low ( $S_t = 0$ ) and high ( $S_t = 1$ ) risk regimes. The kernel densities are based on the 50,000 retained draws from the Gibbs sampler.

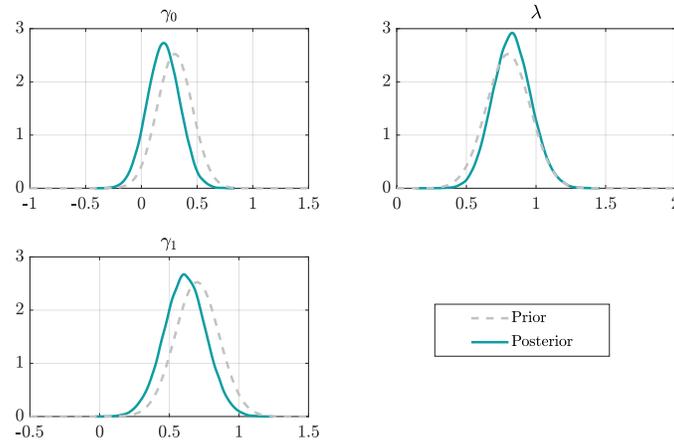


Figure B.8: Probit model: prior and posterior distributions ( $z_{t-1} = \text{cSRI}$ )

Note: The figure shows the prior and posterior distribution of the parameters in the Probit equation. Recall that the probit model is given by  $S_t^* = \gamma_0 + \lambda z_{t-1} + \gamma_1 S_{t-1} + u_t$ . The kernel densities are based on the 50,000 retained draws from the Gibbs sampler.

## B.2.2 Extended set of results

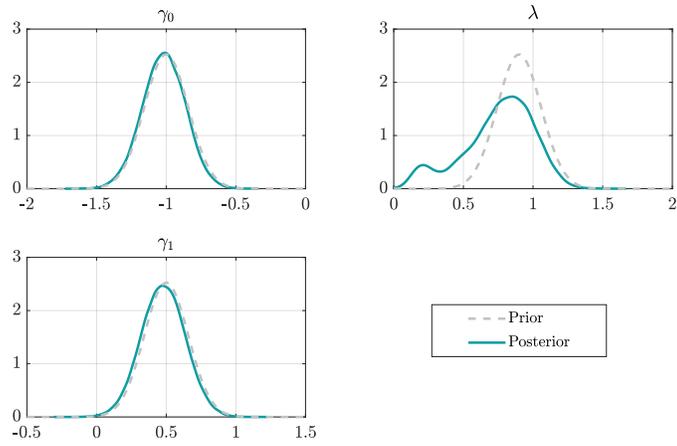


Figure B.9: Probit model: prior and posterior distributions ( $z_{t-1}$  = credit gap)  
 Notes: Recall that the probit model is given by  $S_t^* = \gamma_0 + \lambda z_{t-1} + \gamma_1 S_{t-1} + u_t$

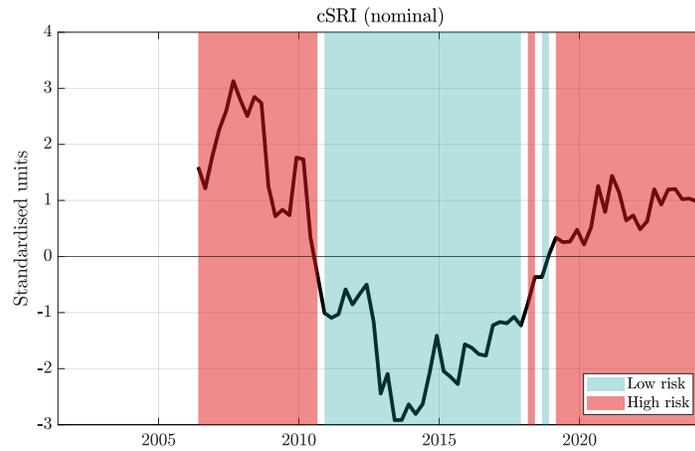


Figure B.10: Risk regimes of the nominal cSRI based on the Markov-Switching model  
 Notes: The red shaded regions denote the high risk regime, based on a 60% probability threshold. The cSRI is available from 2006Q1 onwards.

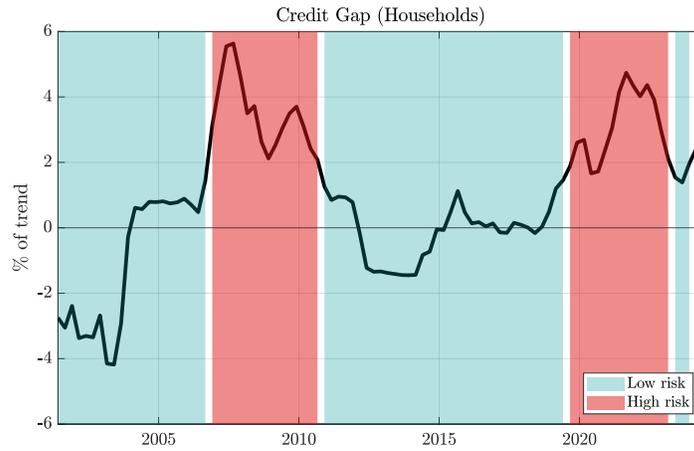


Figure B.11: Risk regimes of the household credit gap based on the Markov-Switching model

Notes: The red shaded regions denote the high risk regime, based on a 60% probability threshold. The 80% probability interval denotes the range between the 10<sup>th</sup> and 90<sup>th</sup> percentiles of the credit gap distribution.

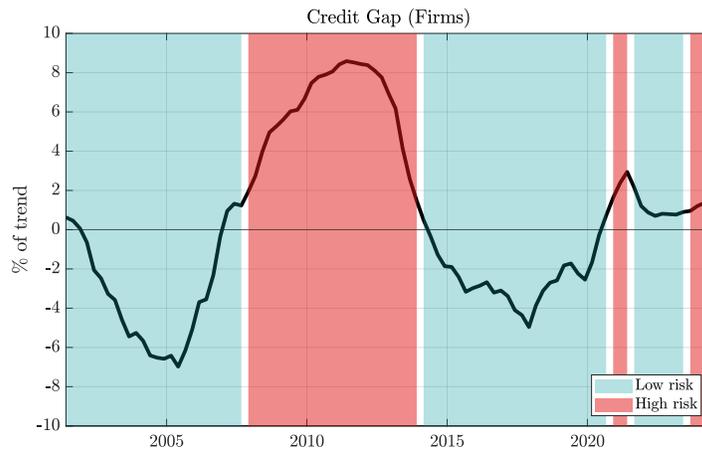


Figure B.12: Risk regimes of the firm credit gap based on the Markov-Switching model

Notes: The red shaded regions denote the high risk regime, based on a 60% probability threshold. The 80% probability interval denotes the range between the 10<sup>th</sup> and 90<sup>th</sup> percentiles of the credit gap distribution.