

Gatt, William

Working Paper

A semi-structural credit gap for Malta: A multivariate filter approach

CBM Working Papers, No. WP/04/2024

Provided in Cooperation with:

Central Bank of Malta, Valletta

Suggested Citation: Gatt, William (2024) : A semi-structural credit gap for Malta: A multivariate filter approach, CBM Working Papers, No. WP/04/2024, Central Bank of Malta, Valletta

This Version is available at:

<https://hdl.handle.net/10419/301977>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



BANK ĊENTRALI TA' MALTA
EUROSISTEMA
CENTRAL BANK OF MALTA

CENTRAL BANK OF MALTA WORKING PAPER



BANK ĊENTRALI TA' MALTA
EUROSISTEMA
CENTRAL BANK OF MALTA

A semi-structural credit gap for Malta:

A multivariate filter approach*

William Gatt[†]

WP/04/2024

*I would like to thank Leonardo Del Vecchio and Massimo Molinari from the Banca d'Italia for their very helpful review of the paper, as well as Alan Cassar, Massimo Giovannini, Marco Ratto, Andrew Spiteri, Wendy Zammit and participants in research seminars held at the Central Bank of Malta and Malta Financial Services Authority for helpful comments and suggestions. I thank Andrew Spiteri for providing some of the data used in this paper, and Diego Rodriguez Palenzuela and Yiqiao Sun from the ECB for sharing the euro area output gap estimates from their paper ([Morley et al., 2023](#)), which I reproduce. Any errors are my own.

The views expressed in this paper are the author's own and do not necessarily reflect the views of the Central Bank of Malta. Correspondence: publicrelations@centralbankmalta.org.

[†]Manager, Financial Stability Research Office, Central Bank of Malta and External Research Fellow, Centre for Finance, Credit and Macroeconomics, University of Nottingham.

Abstract

This paper presents a credit gap for Malta derived from a semi-structural multivariate filter. This modelling approach has several advantages over univariate approaches typically used, for example to construct the Basel gap. The multivariate filtering of observed data into trends and cycles is informed by economic relationships, making estimates of gaps more sensible and robust, and the framework is flexible, allowing for further model development with relative ease. The estimated credit gap is cyclical with an average duration of 13 years, it was positive between the years 2006–2013, and has turned positive again since 2019. The model also provides estimates of other economic concepts like potential output, trend inflation and the house price gap. The semi-structural credit gap estimated in this paper correlates with other existing measures of cyclical risks and is shown to have early warning properties. Moreover, the gap can be decomposed into contributions from the household and firm sectors, yielding a better picture of the drivers of the financial cycle, thereby guiding policy on the appropriate macroprudential policy tool to deploy.

JEL Classification: C11, C32, C51, E32, E44, E58, G51

Keywords: Credit gap, semi-structural model, multivariate filter, Bayesian estimation, Basel gap, house prices

Contents

1	Introduction	4
2	Brief literature review	6
2.1	Univariate approaches	7
2.2	Multivariate approaches	8
3	The model	9
3.1	The real economy block	10
3.2	The consumer and house price block	11
3.3	The credit block	12
3.4	The euro area block	13
4	Estimation details	14
4.1	Calibrated parameters	14
4.2	Bayesian estimation	16
5	Results	18
5.1	Trends and cycles	18
5.2	The aggregate credit gap	21
5.3	Dynamic properties of the model	24
5.4	Early warning properties	25
6	Robustness	29
6.1	Benchmarking with other gaps	29
6.2	Revisions due to end-point bias	31
6.3	The effect of the pandemic on the estimated gap	32
6.4	The credit gap vs. the credit-to-GDP gap	33
7	Policy implications and conclusion	35
	Appendix A Data	42
	Appendix B Parameters	43
	B.1 Calibrated shocks	43
	B.2 Priors and posteriors	43
	Appendix C Other figures	49

1 Introduction

The conduct of macroprudential policy relies on a robust set of indicators which can give insight on the state of the financial cycle. Expansions in the financial cycle are associated with the accumulation of risks, which may eventually reach a tipping point, leading to a financial crisis. Indeed, internationally one out of every three private sector credit booms has historically ended in a banking crisis (Dell’Ariccia et al., 2014). However, while in the setting of monetary policy there exists an observed measure of consumer price inflation which acts as the primary indicator of price stability, there is no corresponding observable that readily signals financial stability risks. Although studies show that credit and asset price developments can be used to systematically predict the likelihood of an ensuing crisis (Schularick and Taylor, 2012; Greenwood et al., 2022), raw credit and house price growth figures in practice may not always indicate to what extent such growth is ‘excessive’.¹ The Basel gap, defined as the deviation of the credit-to-GDP ratio from its one-sided Hodrick-Prescott (HP) filtered trend, is one such attempt at this classification. This measure is accepted as a common reference guide for the state of the financial cycle (Basel Committee, 2010), and is documented to perform well in the prediction of systemic banking crises relative to other univariate approaches (Drehmann et al., 2010; Drehmann and Yetman, 2018).

However, the Basel gap is not without its limitations. Since it involves expressing credit as a ratio of GDP, it has been negatively correlated with GDP growth for some countries in the past, suggesting tighter capital requirements during periods of slow growth, and vice versa (Repullo and Saurina, 2011). This potentially amplifies rather than dampens the pro-cyclicality between downturns and risk.² The use of the one-sided HP filter also has a well-known ‘over-shooting’ problem; following a strong rise in the credit-to-GDP ratio, the trend becomes biased upwards even if the credit-to-GDP ratio stabilises or falls (Lang and Welz, 2017). This is due to the large smoothing parameter that is used and leads to large and persistent negative gaps for several countries, including Malta, and limits its use (see Figure 1).³ In Malta, this effect is caused by the financial liberalisation that took place in the 1990s, which led to strong credit growth relative to GDP, causing the credit-to-GDP ratio to rise significantly from low levels. This rise then partly reversed during the strong economic boom which started in the mid-2010s, lowering the ratio from a peak of around 120% in 2012 to around 75% by the start of 2023. This limits the usefulness of the Basel gap in the local context, as “countercyclical measures are only as good as the financial cycle estimates they rely on” (Alessandri et al., 2022, p.626).

Although the Basel gap is the suggested reference indicator to calibrate the Counter-Cyclical Capital Buffer (CCyB), the Basel Committee on Banking Supervision highlights that any such assessment should not rely entirely and mechanically on this gap but should be supplemented

¹Indeed, while Greenwood et al. (2022) extract a risk threshold to flag red zones for household credit and house price growth based on a panel of countries, in practice this is of limited use to a policymaker concerned with the intricacies and specific structure of the domestic economy. This is more so since, even within their available panel of countries, the threshold is documented to give false alarms and undetected crises as false negatives.

²Moreover, using GDP as a numeraire potentially masks concentration of either credit or economic activity in a single or a few sectors, and passes off developments as spanning across many sectors.

³See also the discussion in Detken et al. (2014), Baba et al. (2020), Karagedikli and Rummel (2020) and Alessandri et al. (2022).

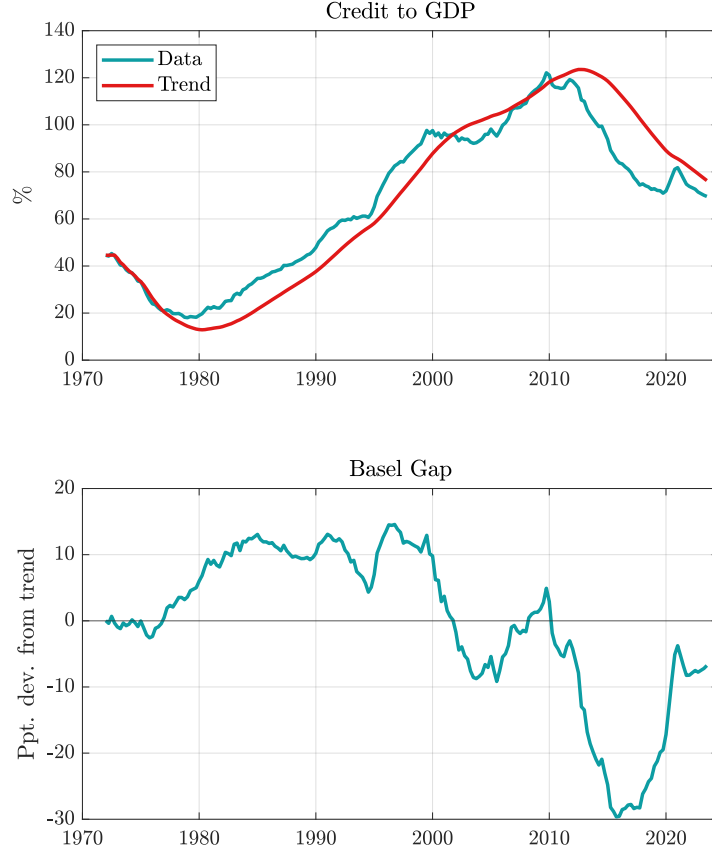


Figure 1: The Basel Gap for Malta

Notes: The trend and implied Basel gap are sourced from the Central Bank of Malta's announcement *The Countercyclical Capital Buffer Rate*, dated December 2023 (Central Bank of Malta, 2023). GDP is expressed as a four-quarter moving sum and the trend is estimated using data from 1972Q1 up to 2023Q3.

with judgement, taking into account any other relevant information. Indeed, the Central Bank of Malta publishes updates to its assessment of the appropriate CCyB rate every quarter, which include the estimated Basel gap on bank credit data together with an array of supplementary indicators to justify its conclusions. A promising indicator which was recently developed is the cyclical Systemic Risk Indicator (cSRI) (Vella, 2024), a composite indicator informed by developments in bank credit, total debt, the debt servicing ratio and the house price-to-income ratio. The cSRI has been shown to possess good early warning properties, but is nonetheless a statistical indicator, and therefore needs to be supplemented with more judgement in its day-to-day use.

This paper documents a semi-structural model based on a multivariate filter approach to derive a measure of the credit gap which proxies the financial cycle, and therefore serves as an early warning indicator. The use of a multivariate approach has several advantages worth highlighting. Firstly, the decomposition of observed data into trends and cycles is not merely statistical but is informed by economic theory via the cross-equation restrictions which are imposed. This gives the model a structural flavour and sets it apart from other filters commonly

used in policymaking. Consequently, this approach delivers a credit gap which is informed by developments in several macro-financial variables, and this is argued to lead to better estimates of the financial cycle (Behn et al., 2013; Detken et al., 2014; Drehmann and Yetman, 2021). Secondly, Laxton et al. (2019) show that latent variables derived from a multivariate filter tend to be more sensible and robust real time estimates relative to those derived from an HP filter, and are subject to smaller historical revisions as more data becomes available. Thirdly, the framework is flexible and allows for relatively easy further model development and refinement in the future if these become necessary. Semi-structural models are increasingly being used in policy institutions to extract unobserved economic variables such as the output gap (Jarociński and Lenza, 2018; Tóth, 2021; Guillochon and Le Roux, 2023; Hasenzagl et al., 2023), the natural interest rate (Laubach and Williams, 2003; Lubik et al., 2015; Holston et al., 2017; Carvalho, 2023) and the credit gap (Laxton et al., 2019; Karam et al., 2021).

The semi-structural credit gap estimated in this paper is cyclical, with an average duration of 13 years per cycle, which is in line with the literature on financial cycles.⁴ It indicates that total credit was below trend in the early 2000s, turning positive later that decade, after which it turned negative although at low levels in absolute terms during most of the 2010s. The gap turned sharply positive again in 2020 and remains positive, although on a declining trend until mid-2023. A pervasive concern that plagues the assessment of any new indicator of cyclical risks in Malta is the lack of a crisis event in the recent past. Indeed, the systemic crises database of Lo Duca et al. (2017) only shows a period of elevated financial stress spanning between August 2009 and November 2012 but does not classify this as a period of a systemic crisis. The credit gap estimated in this paper indeed starts to rise before and then reaches a peak during this period, confirming its ability to signal risks ahead of time. The semi-structural credit gap therefore supplements the set of existing tools used in the macroprudential policy formulation process at the Central Bank of Malta. The model also provides estimates of other economic concepts like potential output, trend inflation and the house price gap, providing a richer and more complete picture of economic developments to policymakers.

The rest of the paper is structured as follows. Section 2 reviews the univariate and multivariate approaches typically used by researchers to extract unobserved variables, Section 3 documents the equations of the model that characterise the multivariate filter, while Section 4 explains the calibration and estimation process of the model’s parameters. The key outputs of the multivariate filter are presented in Section 5 and a battery of robustness tests are documented in Section 6. Finally, Section 7 comments on some policy implications brought about by the semi-structural credit gap and concludes.

2 Brief literature review

The literature on the measurement of unobserved trends and cycles is broad and covers different applications, but is most notably applied to the estimation of the output gap as a measure of the business cycle. In this paper the focus is primarily on the measurement of the financial cycle, proxied by credit gaps. Baba et al. (2020) and Gatt (2024) provide a survey of several

⁴See, for instance, Lang and Welz (2018) and Strohsal et al. (2019).

indicators explored in the literature to track the financial cycle. These indicators are either obtained through the use of univariate time series approaches or derived from multivariate frameworks, which are more involved. I briefly discuss each of these below.

2.1 Univariate approaches

The Basel Committee on Banking Supervision established the use of the so-called Basel gap as a common reference guide in the setting of the Counter-Cyclical Capital Buffer (CCyB), the latter being an element of the Basel III framework. The Basel gap is defined as the deviation of a country’s aggregate credit-to-GDP ratio from its trend, estimated using a one-sided Hodrick Prescott (HP) filter with a smoothing parameter (λ) of 400,000 on quarterly data (Basel Committee, 2010). This decision follows the analysis of several indicators by Drehmann et al. (2010), who find that this indicator outperforms other measures, such as credit growth, asset price growth and banking sector profits and losses.⁵ Although the value for λ is much higher than is typically used for macroeconomic time series, it is justified by the established belief that financial cycles are typically three to four times longer than business cycles. Using the one-sided version of the HP filter implies that historical measures of the gap are unaffected by the introduction of more data points over time, unless historical data are revised with new data releases. Although the Basel gap is used to calibrate the CCyB, the Basel Committee on Banking Supervision highlights that any such assessment should not rely entirely and mechanically on this gap, but should be supplemented with judgement taking into account any other relevant information. Furthermore, the principle governing the use of this gap measure as a common reference guide across countries nevertheless states that the gap need not play a dominant role in driving buffer decisions (Basel Committee, 2010, p.3).

The Basel gap has a number of shortcomings. Repullo and Saurina (2011) argue that, due to the use of GDP as a normalising variable, the gap was negatively correlated with GDP growth in the period 1986–2009 for several countries. Therefore, using this measure to guide the CCyB will invariably lead to loosening capital requirements in good times and increasing them during downturns, exacerbating the pro-cyclicality of risk. Alessandri et al. (2015) argue against using a one-sided HP filter and in favour of using a two-sided filter, since the latter uses all available information and dominates in pseudo real-time forecasting exercise in terms of predicting historical crises. Hamilton (2018) criticises the use of the HP filter when applied to the extraction of economically-meaningful gap measures, given that, *inter alia*, it is likely to yield spurious dynamics and the smoothing parameter value typically chosen is not consistent with the assumed underlying statistical process that generates the cycles.⁶ He proposes the use of a univariate linear projection on the variable’s own lags – the so-called Hamilton filter – as a more robust alternative. Building on this argument, Hamilton and Leff (2020) show that this approach performs better in terms of predicting financial crises in several countries, conditional

⁵The use of the credit-to-GDP gap as an early warning indicator was established more than two decades ago; see Borio and Lowe (2002).

⁶See also Schüler (2020) and Karagedikli and Rummel (2020) for related criticisms of the HP filter as applied to the extraction of credit gaps. See Detken et al. (2014) for an analysis of the effect of different values of λ on the credit-to-GDP gap in the euro area, even when using different smoothing parameters for credit and GDP, respectively.

on using a reasonably long data set to estimate this regression.⁷

Drehmann and Yetman (2021) also find that the Hamilton filter performs marginally better than the HP filter, but only when panel estimation methods are used, as country-by-country estimations perform less well in their application to 41 countries for the period 1985-2017. This hints at the importance of international linkages in predicting crises with a common component or with significant cross-country spillovers. Alessandri et al. (2022) propose an algorithm that can improve the performance of the Basel gap by applying a correction factor obtained using a two-sided version of the HP filter. However, this correction does not significantly improve the measurement of the credit gap in real time, and the authors show that a more meaningful improvement is only obtained when this filtering process is augmented with several additional macroeconomic variables.

2.2 Multivariate approaches

A multivariate approach which uses information from several variables can improve estimates of underlying credit gaps or financial cycles (Behn et al., 2013; Detken et al., 2014; Drehmann and Yetman, 2021). Lang et al. (2019) construct an indicator of cyclical systemic risk as a weighted average of several informative macro-financial sub-indicators. The weights are derived as the optimal values that maximise the early warning properties of the indicator of a crisis across euro area countries. The authors show that a contemporaneous rise in the indicator predicts a subsequent slowdown in economic growth by four percentage points, three to four years into the future. Galati et al. (2016) and Rünstler and Vlekke (2018) use a multivariate version of the Structural Time Series Model of Harvey and Koopman (1997) in which the trend of each series follows a random walk with time-varying drift and the cycle follows a stochastic trigonometric function. They apply this model to US and euro area data and show that financial cycles are longer than business cycles, although there is significant heterogeneity across countries. Similarly, Schüler et al. (2015) use a multivariate spectral approach paired with a time-varying aggregation method to extract a composite financial cycle for 13 EU countries as well as for the euro area, sharing similar findings.

Another strand of the literature imposes some theoretical structure on time series models to derive so-called semi-structural models, on which this paper builds. The approach uses a state space model which decomposes observed data into unobserved trend and cycle components, typically focusing on potential output and the output gap, the NAIRU (Non-Accelerating Inflation Rate of Unemployment) and the unemployment gap. Importantly, these unobserved components do not simply follow time series processes, but the equations governing their dynamics are supplemented with additional variables such that the estimates are disciplined by economic theory.⁸ These become known as multivariate filter models and are celebrated for being able to *jointly* estimate economically-meaningful latent variables. Early applications of this approach are presented in Kuttner (1991, 1994), Apel and Jansson (1999), Fabiani and Mestre (2004)

⁷The authors show that even a difference filter applied over several years can perform reasonably well.

⁸For instance, the unemployment gap is partly influenced by the output gap, capturing Okun's relationship.

and Benes and N'Diaye (2004).⁹ A key research effort which originated at the International Monetary Fund (IMF) was the construction of so-called Quarterly Projection Models, used as a forecasting and policy analysis tool by IMF country desks due to their simple structure (Carabenciov et al., 2008). These models adopted a very similar structure to the multivariate filter and were applied to the study of many economies. Benes et al. (2010) and Blagrove et al. (2015) present more recent applications of the multivariate filter for several countries, while Micallef (2016) applies the approach to the Maltese economy, although his model abstracts from macro-financial variables.

Krznar and Matheson (2017) and Karam et al. (2021) extend the basic multivariate filter by including a credit and financial block which links to the real economy, and estimate the model using data for Brazil and the Philippines, respectively. In the case of Brazil, credit and financial shocks played an important role in driving the output gap since the late 1980s. Conversely, Karam et al. (2021) find that in the Philippines there was very little feedback from the financial sector to the business cycle since the early 2000s, likely on account of the low financial development of the country during most of the sample period.¹⁰ Guillochon and Le Roux (2023) show that including financial variables improves measures of the output gap, *inter alia* by increasing its real-time reliability, as well as by containing information which can improve inflation forecasting.

Finally, Lang and Welz (2018) focus exclusively on a household credit block and specify a three equation model which includes the observation equation, a structural equation for the trend component of real household credit and an autoregressive process for the credit gap. The innovation in this setup is that the structural trend equation is derived from a microfounded overlapping generations model, which provides a tight mapping of the unobserved trend with economic fundamentals, including demographics. The authors estimate this model for several euro area countries and extract household credit gaps which last between 15 and 25 years. These gaps are shown to have superior early warning properties compared to the Basel gap and do not suffer from the ‘over-shooting’ problem of the trend discussed above, making them more robust for policy use. Moreover, as the trend is governed by economic fundamentals (as opposed to statistical trends), it allows for a narrative of the changes in the underlying trend. However, their model abstracts from the joint determination of potential output and the equilibrium interest rate, and only focuses on household credit.

3 The model

The framework used in this paper builds on the multivariate filter approach discussed above, extended with a house price block and an external (euro area) block. Euro area variables are denoted with a star. At its heart, it is a state space model with an observation equation that decomposes observed data into trend and cycle components, where the latter are the (unobserved) state variables. The trend and cycle components are characterised by standard time

⁹See also the related method documented in Laxton and Tetlow (1992) and the application in Butler (1996).

¹⁰See Karam et al. (2021, p.6) for more details.

series processes but are supplemented with additional terms which impart a structural flavour.¹¹ These place additional cross-equation restrictions on the system and assist in the identification of economically-meaningful decompositions. All unobserved states can be perturbed by disturbances, and some observation equations also include a stochastic component which captures both potential measurement errors in the data as well as high frequency fluctuations which are not explained by the model. The model has several blocks, discussed in detail below. All observed variables on the left hand side of the observation equations are in logs (except for the unemployment and interest rates), such that cycles are in terms of percentage deviations from trend. All disturbances are modelled as Gaussian i.i.d. shocks, and unless otherwise stated, are considered to be reduced form shocks void of a clear structural interpretation.

3.1 The real economy block

The real economy block is described in equations (1-7) below. Equation (1) declares observed real output Y_t as the sum of potential output \bar{Y}_t , the output gap \tilde{y}_t and a measurement error ε_t^Y . Potential output evolves as a random walk with a growth rate (drift term) g_t^Y , and is influenced also by yearly changes in the non-accelerating inflation rate of unemployment (NAIRU) \bar{U}_t (equation 2). This latter feature captures feedback from developments in the labour market to the economy's productive capacity. The drift term described in equation (3) is the annual growth in potential output and follows an AR(1) process around a fixed long-run annual potential output growth g^Y . The output gap follows an AR(1) process but is also a function of the output gap in the euro area \tilde{y}_t^* , the lagged difference between cyclical inflation in Malta $\tilde{\pi}_t$ and the euro area $\tilde{\pi}_t^*$, capturing changes in competitiveness, as well as the credit gaps for households \tilde{c}_t^h and firms \tilde{c}_t^f , reflecting demand pressures when either household or firm credit is above trend. The terms $\nu_t^{\bar{Y}}$, $\nu_t^{g^Y}$ and $\nu_t^{\tilde{y}}$ capture reduced form shocks to potential output, potential output growth and the output gap, respectively.

$$Y_t = \bar{Y}_t + \tilde{y}_t + \varepsilon_t^Y \quad (1)$$

$$\bar{Y}_t = \bar{Y}_{t-1} + \frac{1}{4}g_t^Y - \theta_1^Y (\bar{U}_t - \bar{U}_{t-4}) + \nu_t^{\bar{Y}} \quad (2)$$

$$g_t^Y = \tau^Y g_{t-1}^Y + (1 - \tau^Y) g^Y + \nu_t^{g^Y} \quad (3)$$

$$\tilde{y}_t = \rho^Y \tilde{y}_{t-1} + \theta_2^Y \tilde{y}_t^* - \theta_3^Y (\tilde{\pi}_{t-1} - \tilde{\pi}_{t-1}^*) + \theta_4^Y \tilde{c}_t^h + \theta_5^Y \tilde{c}_t^f + \nu_t^{\tilde{y}} \quad (4)$$

$$U_t = \bar{U}_t + \tilde{u}_t + \varepsilon_t^U \quad (5)$$

$$\bar{U}_t = \bar{U}_{t-1} - \theta_1^U \sum_{i=0}^3 \tilde{y}_{t-i} + \nu_t^{\bar{U}} \quad (6)$$

$$\tilde{u}_t = \rho^U \tilde{u}_{t-1} - \theta_2^U \tilde{y}_{t-1} + \nu_t^{\tilde{u}} \quad (7)$$

Equation (5) decomposes the observed unemployment rate into the NAIRU and cyclical unemployment \tilde{u}_t , as well as a measurement error ε_t^U . The NAIRU follows a random walk process but is negatively related to the yearly output gap, such that a persistent economic boom exerts

¹¹Typically, latent variables which represent non-stationary trends are modelled as unit root processes, while the cyclical components are modelled as AR(1) processes, reflecting their stationarity but allowing for significant persistence.

downward pressure on the equilibrium level of unemployment through the creation of employment opportunities (equation 6). The unemployment rate gap in equation (7) follows an AR(1) process and is negatively related to the first lag of the output gap, capturing a delayed Okun relationship. Both the NAIRU and the unemployment rate gap are subject to i.i.d. disturbances.

3.2 The consumer and house price block

The second block of the model describes the evolution of consumer and residential property prices in Malta (equations 8–14). Consumer price inflation π_t is the sum of trend inflation $\bar{\pi}_t$ and transitory inflation $\tilde{\pi}_t$.¹² Trend inflation in Malta follows an AR(1) process around the trend inflation rate in the euro area $\bar{\pi}_t^*$, and can also be driven by shocks $\nu_t^{\bar{\pi}}$. The inflation rate gap $\tilde{\pi}_t$ also follows an AR(1) process but is also a function of the lagged output gap as well as the change in the output gap, capturing a reduced-form Phillips relationship. The inflation gap in the euro area also plays a role in driving transitory inflation in Malta, capturing the transmission of import price pressures. Transitory inflation shocks $\nu_t^{\tilde{\pi}}$ can also drive the inflation gap in Malta.

$$\pi_t = \bar{\pi}_t + \tilde{\pi}_t \quad (8)$$

$$\bar{\pi}_t = \rho_1^{\bar{\pi}} \bar{\pi}_{t-1} + (1 - \rho_1^{\bar{\pi}}) \bar{\pi}_t^* + \nu_t^{\bar{\pi}} \quad (9)$$

$$\tilde{\pi}_t = \rho_2^{\tilde{\pi}} \tilde{\pi}_{t-1} + (1 - \rho_2^{\tilde{\pi}}) (\theta_1^{\tilde{\pi}} \tilde{y}_{t-1} + \theta_2^{\tilde{\pi}} (\tilde{y}_t - \tilde{y}_{t-1}) + \theta_3^{\tilde{\pi}} \tilde{\pi}_t^*) + \nu_t^{\tilde{\pi}} \quad (10)$$

$$P_t^h = \bar{P}_t^h + \tilde{p}_t^h + \varepsilon_t^{P_h} \quad (11)$$

$$\bar{P}_t^h = \bar{P}_{t-1}^h + \frac{1}{4} g_t^{P_h} + \theta_1^{P_h} (\bar{Y}_t - \bar{Y}_{t-4}) + \nu_t^{\bar{P}_h} \quad (12)$$

$$g_t^{P_h} = \tau^{P_h} g_{t-1}^{P_h} + (1 - \tau^{P_h}) g^Y + \nu_t^{g^{P_h}} \quad (13)$$

$$\tilde{p}_t^h = \rho^{P_h} \tilde{p}_{t-1}^h + \theta_2^{P_h} \tilde{y}_{t-1} - \theta_3^{P_h} \tilde{r}_t^h + \nu_t^{\tilde{p}_h} \quad (14)$$

Turning to house prices, the observed real house price level P_t^h is similarly decomposed into a trend and a cycle component, together with a measurement error. Trend house prices \bar{P}_t^h follow a random walk with a drift term $g_t^{P_h}$ and are also affected by yearly changes in potential output together with a disturbance term $\nu_t^{\bar{P}_h}$ (equation 12). Annual growth in trend house prices (equation 13) is driven by an AR(1) process around long run potential output growth, such that real house prices and potential output share a balanced growth path in the long run. The house price gap equation (14) includes an AR(1) term, as well as the lagged output gap and the residential real interest rate gap, defined further below. The output gap proxies demand for housing, which can follow business cycle frequencies, while the real interest rate captures the trade-off between the return on housing as an asset vis-a-vis the return on other investment opportunities.¹³ The house price gap is also subject to shocks $\nu_t^{\tilde{p}_h}$.¹⁴

¹²I do not assume measurement error in headline inflation.

¹³Although the model abstracts from the returns on bank deposits and other assets, these are expected to move in line with the real interest rate on lending as used in the model.

¹⁴Credit developments do not enter directly here, as their inclusion leads to strong feedback and makes the model indeterminate. Nevertheless, credit developments feed into house prices indirectly through their role in

3.3 The credit block

Equations (15)–(22) describe the structure used to decompose real household credit C_t^h and real firm credit C_t^f . I discuss these two variables together since they largely follow the same structure. The observation equations (15) and (16) decompose household and firm credit into familiar trend and cycle components, and measurement errors. The trend components share the typical structure; they both follow random walk processes around growth rates which themselves follow AR(1) processes around the long run growth rate of potential output (equations 17 and 18). Therefore, both credit trends also share a balanced growth path with output and house prices. Trend household credit is also a function of the annual change in the trend of house prices (which in turn grows at the same rate as potential output in the long run), while trend firm credit is a function of the annual change in potential output. These are motivated by the fact that the majority of household credit in the data represent mortgages, which are expected to follow house prices through a collateral channel (Iacoviello, 2005). On the other hand, trend firm credit follows the dynamics of potential output, reflecting derived demand for credit. Deviations of the real interest rates on household and firm credit from their long run averages enter negatively in equations (17) and (18) respectively, capturing the long run cost of credit as a fundamental factor.

$$C_t^h = \overline{C}_t^h + \tilde{c}_t^h + \varepsilon_t^{C_h} \quad (15)$$

$$C_t^f = \overline{C}_t^f + \tilde{c}_t^f + \varepsilon_t^{C_f} \quad (16)$$

$$\overline{C}_t^h = \overline{C}_{t-1}^h + \frac{1}{4}g_t^{C_h} + \theta_1^{C_h} (\overline{P}_t^h - \overline{P}_{t-4}^h) - \theta_2^{C_h} (\overline{RR}_t^h - \overline{RR}^h) + \nu_t^{\overline{C}_h} \quad (17)$$

$$\overline{C}_t^f = \overline{C}_{t-1}^f + \frac{1}{4}g_t^{C_f} + \theta_1^{C_f} (\overline{Y}_t - \overline{Y}_{t-4}) - \theta_2^{C_f} (\overline{RR}_t^f - \overline{RR}^f) + \nu_t^{\overline{C}_f} \quad (18)$$

$$g_t^{C_h} = \tau^{C_h} g_{t-1}^{C_h} + (1 - \tau^{C_h}) g^Y + \nu_t^{g^{C_h}} \quad (19)$$

$$g_t^{C_f} = \tau^{C_f} g_{t-1}^{C_f} + (1 - \tau^{C_f}) g^Y + \nu_t^{g^{C_f}} \quad (20)$$

$$\tilde{c}_t^h = \rho^{C_h} \tilde{c}_{t-1}^h + \theta_3^{C_h} \tilde{p}_{t-1}^h - \theta_4^{C_h} \tilde{r}_t^h + \theta_5^{C_h} \tilde{y}_{t-1} + \nu_t^{\tilde{c}_h} \quad (21)$$

$$\tilde{c}_t^f = \rho^{C_f} \tilde{c}_{t-1}^f - \theta_3^{C_f} \tilde{r}_t^f + \theta_4^{C_f} \tilde{y}_{t-1} + \nu_t^{\tilde{c}_f} \quad (22)$$

Finally, the cyclical components \tilde{c}_t^h and \tilde{c}_t^f (equations (21) and (22)) both follow an AR(1) process, and are both driven by developments in the respective interest rate gaps, as well as the lagged output gap. The household credit gap equation includes also a term for the house price gap, again capturing the role that collateral effects might play in driving cycles in household credit.

The system of equations (23)–(28) below similarly lists the corresponding structure for nominal interest rates on household and firm credit, R_t^h and R_t^f respectively, starting with the decomposition of observed interest rates into trend and gap components.¹⁵ The respective trend components both follow an AR(1) process around trend interest rates in the euro area plus a constant spread (ψ^{R_h} , ψ^{R_f}). The interest rate gaps each also follow an AR(1) process around

driving the output gap.

¹⁵As for inflation, I do not include a measurement error for interest rates.

the interest rate gap in the euro area lagged by one period \tilde{r}_{t-1}^* , multiplied by a coefficient. This coefficient captures the (short-run) pass-through of euro area monetary policy to domestic interest rates, with an implicit assumption that this pass-through is delayed by at least a quarter. Finally, equations (29)–(32) define interest rate trends and gaps in real terms via the Fisher relation, which uses expected (model-consistent) inflation in the next period.

$$R_t^h = \overline{R}_t^h + \tilde{r}_t^h \quad (23)$$

$$R_t^f = \overline{R}_t^f + \tilde{r}_t^f \quad (24)$$

$$\overline{R}_t^h = \rho_1^{R^h} \overline{R}_{t-1}^h + (1 - \rho_1^{R^h}) (\overline{R}_t^* + \psi^{R^h}) + \nu_t^{\overline{R}^h} \quad (25)$$

$$\overline{R}_t^f = \rho_1^{R^f} \overline{R}_{t-1}^f + (1 - \rho_1^{R^f}) (\overline{R}_t^* + \psi^{R^f}) + \nu_t^{\overline{R}^f} \quad (26)$$

$$\tilde{r}_t^h = \rho_2^{R^h} \tilde{r}_{t-1}^h + (1 - \rho_2^{R^h}) \theta_1^{R^h} \tilde{r}_{t-1}^* + \nu_t^{\tilde{r}^h} \quad (27)$$

$$\tilde{r}_t^f = \rho_2^{R^f} \tilde{r}_{t-1}^f + (1 - \rho_2^{R^f}) \theta_1^{R^f} \tilde{r}_{t-1}^* + \nu_t^{\tilde{r}^f} \quad (28)$$

$$\overline{RR}_t^h = \overline{R}_t^h - \mathbb{E}_t\{\pi_{t+1}\} \quad (29)$$

$$\overline{RR}_t^f = \overline{R}_t^f - \mathbb{E}_t\{\pi_{t+1}\} \quad (30)$$

$$\tilde{r}_t^h = \tilde{r}_t^h - \mathbb{E}_t\{\pi_{t+1}\} \quad (31)$$

$$\tilde{r}_t^f = \tilde{r}_t^f - \mathbb{E}_t\{\pi_{t+1}\} \quad (32)$$

3.4 The euro area block

The last block of the model details developments in euro area variables, and follows the same structure as discussed above, with potential output \overline{Y}_t^* following a random walk with a time-varying growth rate $g_t^{Y^*}$. The output gap equation (36) contains an AR(1) component, and a coefficient on the real interest rate gap which captures an intertemporal smoothing motive and follows the structure of a dynamic IS curve.

$$Y_t^* = \overline{Y}_t^* + \tilde{y}_t^* \quad (33)$$

$$\overline{Y}_t^* = \overline{Y}_{t-1}^* + \frac{1}{4} g_t^{Y^*} + \nu_t^{\overline{Y}^*} \quad (34)$$

$$g_t^{Y^*} = \tau^{Y^*} g_{t-1}^{Y^*} + (1 - \tau^{Y^*}) g^{Y^*} + \nu_t^{g^{Y^*}} \quad (35)$$

$$\tilde{y}_t^* = \rho^{Y^*} \tilde{y}_{t-1}^* - \theta_1^{Y^*} (\tilde{r}_t^* - \mathbb{E}_t\{\tilde{\pi}_{t+1}^*\}) + \nu_t^{\tilde{y}^*} \quad (36)$$

$$\pi_t^* = \pi^* + \tilde{\pi}_t^* \quad (37)$$

$$\tilde{\pi}_t^* = \rho_1^{\pi^*} \tilde{\pi}_{t-1}^* + (1 - \rho_1^{\pi^*}) \mathbb{E}_t\{\tilde{\pi}_{t+1}^*\} + \theta_1^{\pi^*} \tilde{y}_{t-1}^* + \theta_2^{\pi^*} (\tilde{y}_t^* - \tilde{y}_{t-1}^*) + \nu_t^{\tilde{\pi}^*} \quad (38)$$

$$R_t^* = \overline{R}_t^* + \tilde{r}_t^* \quad (39)$$

$$\overline{R}_t^* = \rho_1^{R^*} \overline{R}_{t-1}^* + (1 - \rho_1^{R^*}) r^* + \nu_t^{\overline{R}^*} \quad (40)$$

$$\tilde{r}_t^* = \rho_2^{R^*} \tilde{r}_{t-1}^* + (1 - \rho_2^{R^*}) (\theta_1^{R^*} \tilde{\pi}_t^* + \theta_2^{R^*} \tilde{y}_t^*) + \nu_t^{\tilde{r}^*} \quad (41)$$

Trend inflation in the euro area π^* is time-invariant around a long-run target. Therefore, the euro area inflation gap $\tilde{\pi}_t^*$ captures deviations from this target inflation rate. The equation for the inflation gap borrows from the structure of a New Keynesian Phillips curve, with a relative weight on the first lag and expected inflation in the next period, and is also a function of the (lagged) level and change of the euro area output gap \tilde{y}_t^* . Expectations about the long run inflation rate coincide with the ECB’s target π^* , with the expected inflation gap in the future being 0 such that $\pi_t^* = \pi^*$ as $t \rightarrow \infty$. Indeed, the presence of expected inflation in the inflation gap equation stabilizes the dynamics of the model. The trend euro area nominal interest rate follows an AR(1) process around a constant, while the interest rate cycle follows an inertial Taylor rule which includes the inflation gap and the output gap. While the observation equations for euro area variables do not include measurement errors, trends and gaps are all potentially perturbed by disturbances.

Figure 2 summarizes the interaction and linkages between the components of the model as a directed graph. It shows that output, credit, house prices and interest rates are linked via several channels. This representation of the model emphasizes its semi-structural nature, in contrast with multivariate approaches which assume independent dynamics across the variables in the system. For instance, it shows how a rise in the euro area interest rate transmits within the euro area but also to the Maltese economy via retail rates, which then exert an effect on household and firm credit, and house prices, which then in turn impact output and unemployment. Movements in euro area output and inflation also have a direct effect on Maltese output via demand and competitiveness channels. The direction of these links also emphasizes that developments in Malta have no effect back on the euro area, a small country assumption embedded in the model.

4 Estimation details

4.1 Calibrated parameters

Several parameters of the model are econometrically weakly identified or not identified at all, in particular, the variances of the several disturbance terms. This feature is partly expected, given the presence of many more shocks than observables, but is also corroborated by formal identification tests (Iskrev, 2010). It is therefore customary in multivariate filter models to calibrate a subset of parameters and shock processes given these identification issues. The parameters which are calibrated and which either govern the dynamics or the long run behaviour balanced growth path are shown in Table 1. The parameter θ_3^Y , which links developments in domestic inflation relative to that in the euro area, is set to 0.09 as in Micallef (2016). The parameter linking the real interest rate gap to the house price gap $\theta_3^{P_h}$ is set to 0.05, with higher values leading to indeterminacy. The parameter governing the persistence of the growth rate of trend house prices τ^{P_h} proved hard to estimate and led to unstable results, so it was calibrated at the prior mean used for other corresponding parameters at 0.8. The parameters governing the sensitivity of trend household and firm credit to their respective long run real interest rates are both set to 0.2, giving rise to a role for interest rate developments to affect the dynamics of

these trends.¹⁶

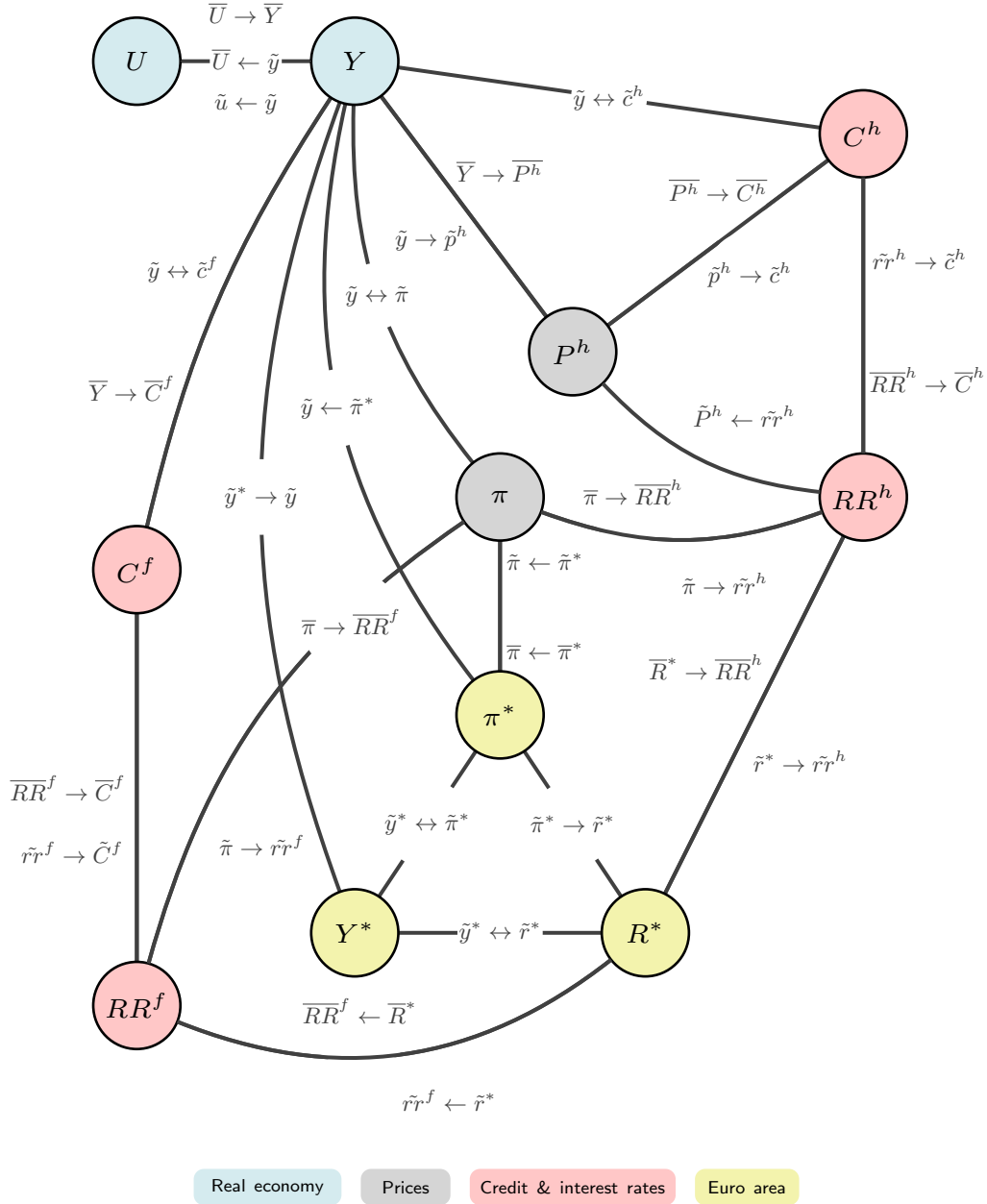


Figure 2: Directed graph for the Multivariate Filter

Notes: The nodes represent the observed variables, while the links capture the relationships between the unobserved components of the model. The arrows point from variables on the right hand side to those on the left hand side of the model's equations.

¹⁶An estimation of the model with lower values for these parameters delivers unreasonably large positive credit gaps from the second half of the sample onwards. This is due to a disconnect between structural developments in long run interest rates, which have declined over time, and credit developments. The trends for credit under this alternate calibration grow at a slower rate, leading to these large positive gaps.

The middle segment of Table 1 reports most of the parameters that relate to the euro area block. All of these are calibrated jointly such that the model yields a response of euro area GDP and inflation to a monetary policy shock – proxied by a shock to the interest rate gap \tilde{r}_t^* , see equation (41) – which is largely in line with the corresponding responses derived from an estimated structural model for the euro area (Coenen et al., 2018).¹⁷ The bottom segment of Table 1 shows the parameters that govern the long run behaviour of the model. The growth rate of Maltese and euro area GDP are calibrated at 4% and 2% respectively, reflecting their long run growth rates over the entire sample.¹⁸ The long run nominal policy rate is also set at its sample average, at 2.5%, while the inflation target of the ECB is set at 2%, in line with its central definition for price stability. The average spreads between loan interest rates and the ECB policy rates are set at 2 percentage points and 3.3 percentage points, respectively, and are based on the average spread during a period of ‘conventional’ monetary policy (2001–2008), reflecting market features during more normal times.

Finally, the list of shock variances which are calibrated can be found in Appendix B. As discussed above, most of these variances are weakly identified or not identified at all and are fixed at values that deliver reasonable variation in the estimated trends and gaps. Part of the calibration process involved cross-checking some implied estimated gaps with estimates from other sources, as discussed further in Section 6.1. The variances of the measurement errors are set such that they explain up to 10% of the movement in the observed data.¹⁹

4.2 Bayesian estimation

I use Bayesian full-information methods to estimate the remaining parameters and shock variances. Let \mathbf{s}_t denote the $N_s \times 1$ vector of the unobserved states of the model (trends and cycles), and \mathbf{y}_t the $N_y \times 1$ vector of observed variables. The linearised rational expectations solution is given by the state space representation:

$$\mathbf{s}_t = \mathbf{A}\mathbf{s}_{t-1} + \boldsymbol{\nu}_t, \quad \boldsymbol{\nu}_t \sim N(0, \mathbf{Q}) \quad (42)$$

$$\mathbf{y}_t = \mathbf{B}\mathbf{s}_t + \boldsymbol{\varepsilon}_t, \quad \boldsymbol{\varepsilon}_t \sim N(0, \mathbf{R}) \quad (43)$$

where $\boldsymbol{\nu}_t$ is a $N_\nu \times 1$ vector of structural shocks with time-invariant variance-covariance matrix \mathbf{Q} of size $N_\nu \times N_\nu$, and $\boldsymbol{\varepsilon}_t$ an $N_\varepsilon \times 1$ vector of shocks that capture measurement errors. The time-invariant matrix \mathbf{R} is of size $N_\varepsilon \times N_\varepsilon$, and both variance-covariance matrices are assumed to be diagonal. Equation (42) is the transition equation, which captures all the equations of the model that govern the dynamics of trends and cycles. Equation (43) is the observation equation,

¹⁷Recall that the euro area block is semi-structural, and the parameters linking the response of the interest rate *gap* to developments in inflation and the output gap do not correspond directly to estimates for Taylor rules estimated for the euro area, since the latter are typically estimated on observed policy rates rather than their deviation from the trend component.

¹⁸These growth rates imply that Malta’s potential GDP level would eventually catch up with and exceed that of the euro area over a very long simulation period. However, this is not an issue for this application, as the model is only intended to be used to decompose trends and cycles in-sample, and perhaps for short-run forecasting over a few quarters. Estimating the model with a growth rate of 2% leads the trends to progressively grow at a slower rate than the data, leading to positive gaps which persistently widen.

¹⁹See Adolfson et al. (2013) and Schmitt-Grohé and Uribe (2012) for similar applications.

Table 1: Key calibrated parameters

Parameter	Value	Comment
Dynamics - domestic block		
θ_3^Y	0.09	Sensitivity of \tilde{y}_t to $\tilde{\pi}_{t-1} - \tilde{\pi}_{t-1}^*$
$\theta_3^{P_h}$	0.05	Sensitivity of \tilde{p}_t^h to \tilde{r}_t^h
τ^{P_h}	0.80	AR(1) coefficient on $g_t^{P_h}$
$\theta_2^{C_h}$	0.20	Sensitivity of \tilde{C}_t^h to $\overline{RR}_t^h - \overline{RR}^h$
$\theta_2^{C_f}$	0.20	Sensitivity of \tilde{C}_t^f to $\overline{RR}_t^f - \overline{RR}^f$
Dynamics - euro area block		
$\theta_1^{Y^*}$	0.35	Sensitivity of \tilde{y}_t^* to $\tilde{R}_t^* - \mathbb{E}_t\{\tilde{\pi}_{t+1}^*\}$
τ^{Y^*}	0.96	AR(1) coefficient on $g_t^{Y^*}$
ρ^{Y^*}	0.82	AR(1) coefficient on \tilde{y}_t^*
$\rho_1^{\pi^*}$	0.58	AR(1) coefficient on $\tilde{\pi}_t^*$
$\theta_1^{\pi^*}$	0.06	Sensitivity of $\tilde{\pi}_t^*$ to \tilde{y}_{t-1}^*
$\theta_2^{\pi^*}$	0.25	Sensitivity of $\tilde{\pi}_t^*$ to $\Delta\tilde{y}_t^*$
$\rho_1^{R^*}$	0.50	AR(1) coefficient on \tilde{R}_t^*
$\rho_2^{R^*}$	0.85	AR(1) coefficient on \tilde{R}_t^*
$\theta_1^{R^*}$	2.50	Sensitivity of \tilde{r}_t^* to $\tilde{\pi}_t^*$
$\theta_2^{R^*}$	2.25	Sensitivity of \tilde{R}_t^* to \tilde{y}_t^*
Stationary equilibrium		
g^Y	4.00	Long run growth rate of output
g^{Y^*}	2.00	Long run growth rate of EA output
ψ^{R_h}	2.00	Spread between \overline{R}^h and \overline{R}^*
ψ^{R_f}	3.30	Spread between \overline{R}^f and \overline{R}^*
r^*	2.50	EA average nominal policy rate
π^*	2.00	Central ECB target

Note: Δ indicates the first difference.

and captures all equations that decompose observed data into trend and cycle components. The elements of \mathbf{A} are functions of the structural parameters, while the elements of \mathbf{B} map the model states to the observables.²⁰

I use eleven observables in the estimation process, corresponding to each trend-cycle decomposition performed by the model, for the period 2000Q1 to 2019Q4 to avoid including data spanning the COVID-19 pandemic, which can greatly influence the estimates. These eleven observables are real GDP, the unemployment rate, annual HICP inflation, real house prices, real credit to households, real credit to firms, interest rates on household and firm credit for Malta, and real GDP, annual HICP inflation and the ECB policy rate (proxied by the shadow short rate of Krippner (2020)), for the euro area. Full details about data sources and transformations can be found in Appendix A. I use the slice sampler (Neal, 2003) as discussed and implemented in Planas et al. (2015) using Dynare 6.1 (Adjemian et al., 2024). I run the slice

²⁰A necessary requirement for likelihood-based estimation of the model's parameters is that $N_\nu + M_\varepsilon \geq N_y$, otherwise the system is singular.

sampler with 10 independent chains of 7,000 draws each, retaining the last 4,000 draws from each chain to approximate the posterior distributions of the parameters.²¹ The first four years of data are used to initialize the states in the diffuse Kalman filter, while data for the period 2004Q1–2019Q4 are used in the estimation of the parameters. The posterior distributions are summarized in Appendix B.

5 Results

5.1 Trends and cycles

The key object of interest of the model is the smoothed estimates of the states using the Kalman filter, given the parameters of the model. Smoothed estimates are preferred since they use all available information to deliver the best assessment of developments in the data at a given time period.²² Since I use a Bayesian approach, these states are defined by a *distribution* of outcomes at each point in time, which in this paper is summarized by the 10th and 90th percentiles. This distribution conveys useful information on the uncertainty around the trend and cycle estimates, allowing for a probabilistic assessment of events. I run the Kalman smoother on all the data used in this study (2000Q1–2023Q2), conditional on the estimated posterior distributions. Figures 3 and 4 show the estimated trends and cycles, respectively, for the six key macroeconomic variables for Malta, while Figure 5 decomposes some of these trends into their determinants. The measurement error included in several observation equations largely plays a minor role, mostly leading to smoother time series for the observed data. However, the unemployment rate as fitted by the model is more volatile around the incidence of the COVID-19 pandemic, falling more towards the end of 2019 but then jumping up for a few quarters more before falling back down.

Potential output growth was relatively stable in the first half of the sample but then accelerated in the second half on the back of an economic boom, while the observed unemployment rate and the NAIRU both fell.²³ The pandemic had a noticeable effect on both potential output, which barely grew in this period, and the NAIRU, which shot up by around a percentage point. Trend inflation in Malta stabilized at low levels in the mid-2010s compared to the previous decade, likely as a result of government policies which provided for more stable energy prices and later commodity prices. Trend inflation then rose towards the 2% level as in the euro area, before rising further on account of the global inflationary shocks towards the end of the sample.

The trends in residential house prices, household and firm credit generally experienced more fluctuations, leading to time-varying growth rates. Trend house prices grew by 4–6% in yearly

²¹Trace plots indicate that a much lower number of draws per chain suffices for convergence for most parameters, while others, in particular the variance of the shock of the house price gap, require more draws.

²²Some policymakers may be averse to using two-sided filters due to their potential for end-point bias and revisions over subsequent new data points. While this property is a feature of this method, it should not discourage users from seeking the best possible estimation of an unobserved state, *especially* when used to inform the best course of action. Nevertheless, in section 6.2 I show that the scale of these revisions historically tended to be low, alleviating these concerns.

²³Several factors may be behind this, including emphasis on labour re-training, lifelong learning programmes, and the tapering of unemployment benefits, amongst others.

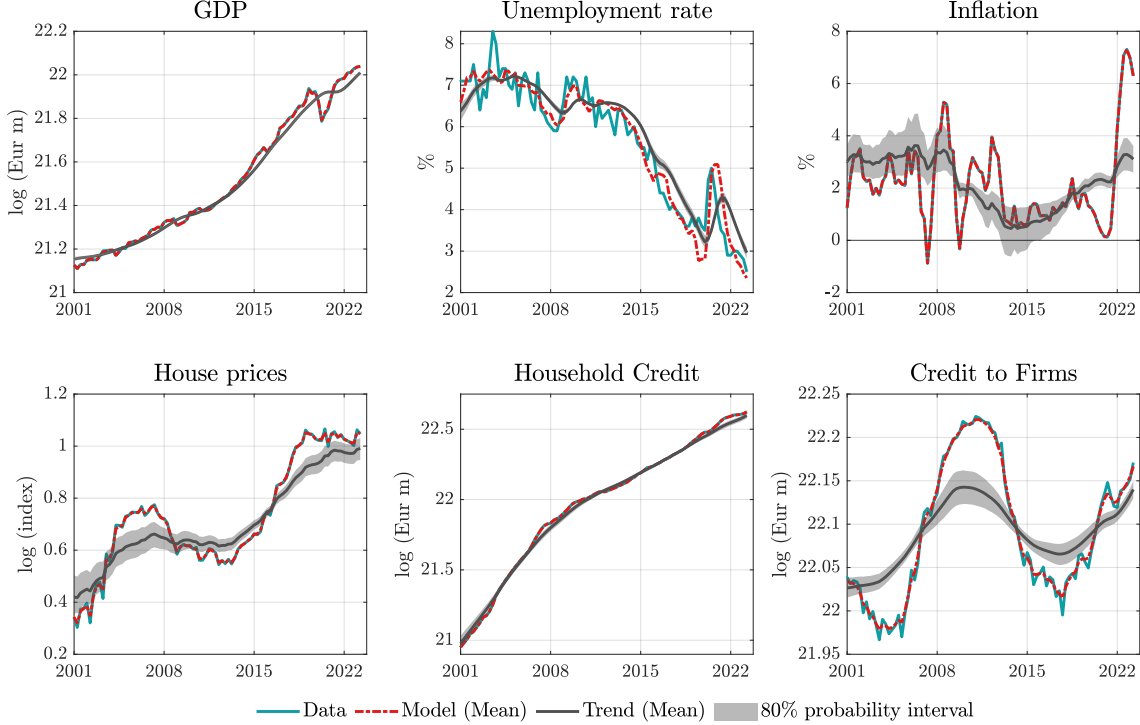


Figure 3: Actual data and trends

Notes: The difference between variables denoted as Data and Model is due to the measurement error. The trends are the smoothed state estimates over the entire sample period. The 80% probability intervals are the credible intervals given by the 10th and 90th percentiles of the distributions of the trends.

terms in the early 2000s but then slowed down and experienced a mild contraction around the onset of the Great Financial Crisis. Trend house prices then accelerated again on the back of the economic boom in the second half of the sample (see Figure 5).²⁴ The dynamics of credit to households and firms differ throughout the sample; while trend household credit grew strongly in the first half of the sample and then settled at somewhat lower growth rates in the second, trend credit to firms experienced cycles reflecting stages of leveraging and deleveraging. The decomposition shown in Figure 5 shows that the real interest rate played a significantly greater role in driving these leverage cycles, despite the robust growth in potential output in the second half of the sample.²⁵ Indeed, during this time a number of firms shifted to debt issuance as an alternative to bank financing, driven *inter alia* by tighter bank lending standards and more favourable capital market conditions characterised by ample investor liquidity and a low interest rate environment (Darmanin, 2017; Central Bank of Malta, 2018). Meanwhile, trend household credit followed the developments in the housing market, with the real interest rate playing a relatively lesser role. The trends for house prices and credit appear to be largely

²⁴The estimated house price trend is still relatively noisy despite the inclusion of a measurement error in the observation equation. As shown in Figure 5, these high frequency fluctuations are not attributable to any economic force and are therefore captured by the ‘shocks’ component.

²⁵The analysis in this paper focuses on aggregate credit to firms, and therefore does not capture idiosyncrasies across sectors.

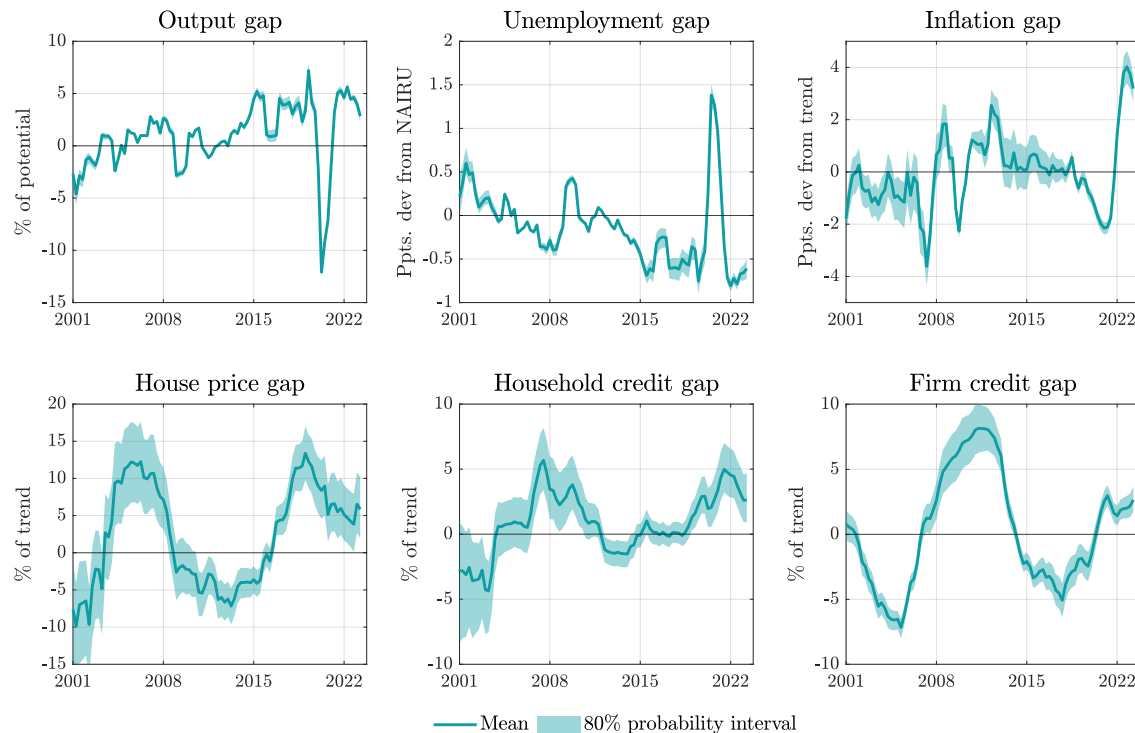


Figure 4: Cycles

Notes: The cycles are the smoothed state estimates over the entire sample period. The 80% probability intervals are the credible intervals given by the 10th and 90th percentiles of the distributions of the cycles.

unaffected by the pandemic, most likely due to the various government support policies which were implemented at the time.

These results give a coherent account of developments in the Maltese economy over the recent past which can be surmised from Figure 4; an economic boom starting around 2013 led to strong demand for labour during a period of relatively weak inflationary pressures. Price pressures instead materialised in the residential property market, which saw prices rising faster than trend as from 2016, giving rise to a positive household credit gap since 2018. On the other hand, the firm credit gap was negative during most of this period following a period of deleveraging as discussed above. Towards the end of the sample both household and firm credit gaps were positive, although in the latter the gap is far from the peak reached in the early 2010s. The results for the house price gap are in line with those presented in [Gatt and Grech \(2016\)](#), who study the housing market and show that house prices were below trend in the early 2000s, peaking above trend in 2005–2006, and subsequently correcting and remaining below trend up to 2015.

An interesting finding is the correlation between the house price gap and the household credit gap. The left panel in Figure 6 superimposes these two gaps, and shows that the household credit gap tends to follow the house price gap with a lag. The right panel confirms this; the contemporaneous correlation coefficient between these two gaps is 0.6, but rises further when

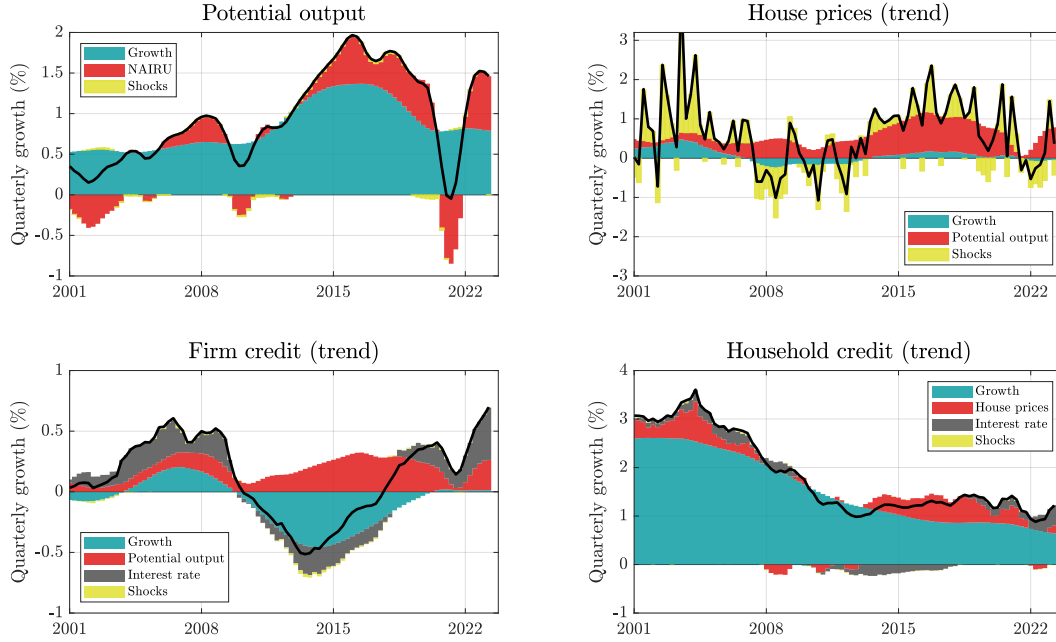


Figure 5: Drivers of trend growth

Notes: The black line shows the quarterly change in each trend. The decomposition is based on the equations for the trends and evaluated at the posterior means of the estimated parameters.

the house price gap is lagged.²⁶ Although this co-movement is to a certain extent hard-coded into both the trend and cycle of household credit in the model, it appears to be a feature that exists in the data.²⁷ This result is consistent with the findings of Igan et al. (2009), who show that house prices tend to lead credit in the majority of advanced and emerging countries they include in their study, and points to the role of housing collateral in driving household credit in the Maltese economy. Therefore, the house price gap itself is likely to have predictive potential for household credit cycle developments.

5.2 The aggregate credit gap

The household and firm credit gaps can be merged to form the economy-wide credit gap, which is the primary result of this paper. However, they are derived in real terms using different deflators, so they cannot simply be added together. Instead, I derive the aggregate credit gap by transforming the observed levels of household and firm credit, which are in real terms, back to nominal terms using the respective price indices (see Appendix A). I repeat this for the

²⁶That is, the household credit cycle as at time t is correlated with developments in the house price cycle which have already taken place (at time $t - k$).

²⁷Using simpler univariate filters, such as a quadratic time trend and the Hamilton filter (not shown), on both house prices and household credit delivers qualitatively similar conclusions.

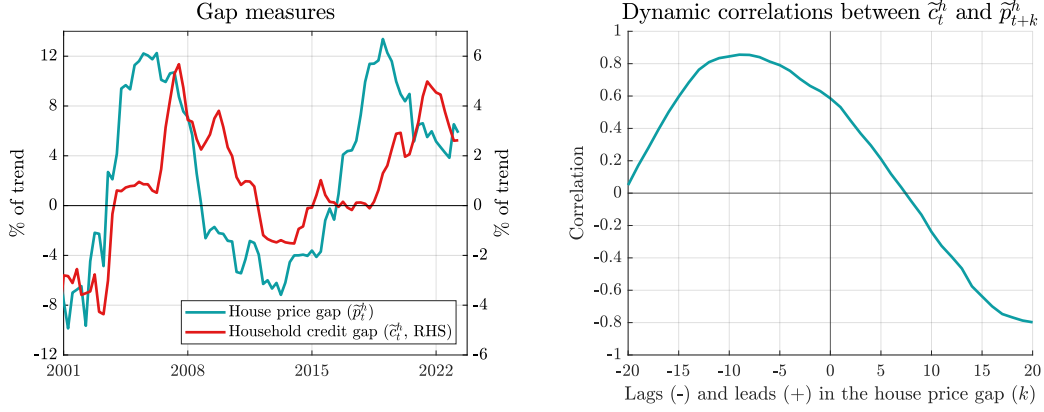


Figure 6: The relationship between house price and household credit cycles

Notes: The panel on the left shows the time series of the mean house price and household credit gaps, while the right panel shows the correlations between the household credit gap and different quarterly lags and leads of the house price gap.

distribution of the estimated trends for household and firm credit, using the same price indices.²⁸ The aggregate credit gap is then the deviation of total observed credit less the economy-wide trend, and is shown in Figure 7.

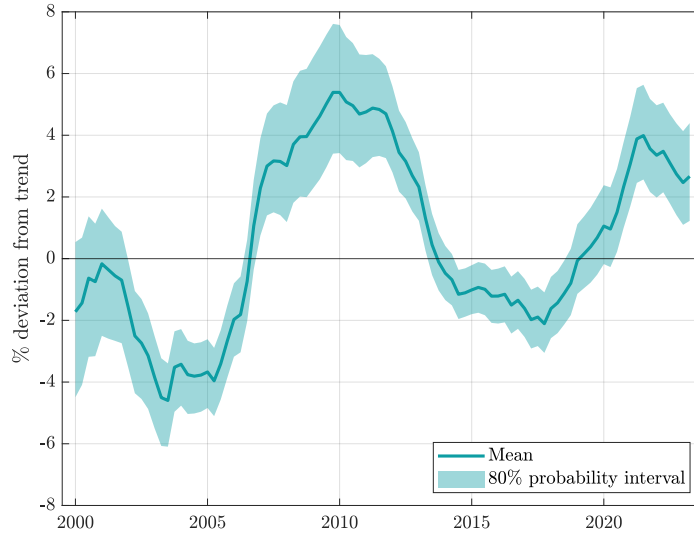


Figure 7: The aggregate credit gap

Notes: The figure shows the deviation of total nominal credit to households and firms from the inferred distribution of the economy-wide trend. The bands are formed using the 10th and 90th percentiles.

The aggregate credit gap is cyclical and over the past 20 years fluctuated between -6% and

²⁸Using the actual price indices to inflate the estimated trends has the advantage that it avoids introducing a large spike in the aggregate gap in 2022–2023.

8%. The duration of the cycle is about 13 years, in line with the literature on financial cycles.²⁹ Total credit was below trend in the early 2000s, turning positive later that decade, after which it turned negative although at low levels in absolute terms during most of the 2010s. The gap turned sharply positive again in 2019 and remains positive – although narrowing – up until 2023Q2. The probability interval reflects the underlying uncertainty about the values of the parameters of the model and the distribution of historical shocks which may have affected the gap, either directly or indirectly via other variables in the model. Towards the end of the sample, the model estimates an 80% probability that the gap was between 1.2% and 4.4% by 2023Q2, with a mean of 2.7%. This conveys a clear signal that the gap was well within the positive range, with credit being above trend. Conversely, even though the mean credit gap stood at -0.7% in 2006Q3, the 80% probability interval puts the gap at being between -2.0% and 0.6%, with less than a 30% probability that the gap was positive. This probability measure communicates the underlying uncertainty around the estimate of an indicator - the fundamental level of credit at any point in time - which is inherently unobservable.

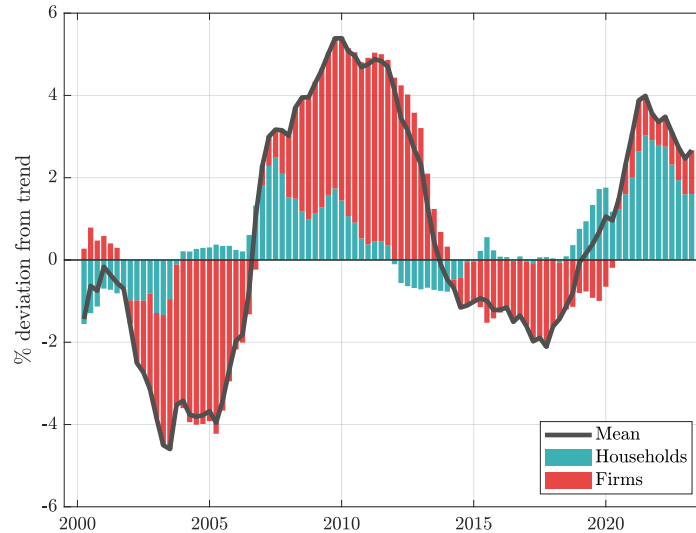


Figure 8: Decomposing the credit gap

Notes: The solid line is the credit gap evaluated at the mean. The contributions are calculated using the sectoral gaps weighted by the share of loans in each sector at each point in time.

The model can also be used to investigate the dynamics of sectoral credit gaps (as shown above) and assess their contribution to the aggregate gap. Figure 8 decomposes the credit gap into contributions from households and firms, focusing only on the mean estimates for ease of reference. Throughout most of the period under study, developments in lending to firms were the key driver of the aggregate credit gap. This is due to two factors. First, the share of loans to firms represented the bulk of loans issued, representing more than 70% of total bank lending in the early 2000s. This ratio fell progressively over the sample period, as growth in household

²⁹See, *inter alia*, [Strohsal et al. \(2019\)](#).

mortgages outstripped growth in loans to firms, reaching 50% by mid-2013, with the share of corporate loans stabilising at around 40% by the end of the sample period. This large historical share attributes more weight to developments in the corporate sector in the overall credit gap. Second, developments in loans to firms were historically more volatile, leading to a gap with higher peaks and lower troughs relative to the household credit gap.

The chart also shows that the household and firm credit gaps are not totally synchronised, with the household gap tending to lead the firm gap. Nevertheless, from 2020 onwards, both gaps were simultaneously positive, although the aggregate credit gap was driven mostly by developments in the household sector, which started registering a small but positive credit gap since 2019. Mortgage growth during this period was supported by strong activity in the housing sector, following the introduction of fiscal incentives during the COVID-19 pandemic. At the same time, credit guarantees to firms, as well as strong activity in the construction and real estate market likely explain the low, but positive, contribution to the aggregate credit gap.

5.3 Dynamic properties of the model

It is instructive to look at the dynamic properties of the gaps following a disturbance to the model, to emphasise the economic interlinkages that drive these cycles. However, given the semi-structural nature of the model, the estimated shocks are of reduced form and, in general, lack a well-defined structural interpretation. Yet, two of these shocks can be reconciled with structural shocks from MEDSEA-FIN, an estimated DSGE model of the Maltese economy which includes housing and a banking sector (Gatt, 2022). The shocks to the euro area interest rate gap in equation (41) (ν_t^{r*}) and the house price gap (14) ($\nu_t^{p_h}$) correlate well with structural monetary policy and housing demand shocks, respectively, obtained from MEDSEA-FIN.³⁰ This allows for a structural interpretation of these two shocks in the multivariate filter. Impulse responses are generated by recursively iterating over the state transition equation (42) for a given draw of the parameters and shock variances from their posterior distributions.

Figure 9 shows the reaction of the key domestic gap measures following a euro area monetary policy shock of +50 basis points.³¹ Monetary policy tightening, which reduces euro area output and inflation gaps (not shown), leads to shallower negative output and inflation gaps in Malta, and triggers a small increase in the unemployment rate gap. These effects are short-lived and last for less than 3 years. This shock also has a very minor impact on house prices and credit, partly due to the low estimated pass-through to domestic interest rates. Nevertheless, the dynamic effects persist for much longer, reflecting the higher persistence of financial variables.

Figure 10 shows the transmission of a typical housing demand shock, which raises house prices by around 2 percentage points relative to trend on impact. There is a delayed but highly persistent effect on household credit, which feeds off directly from the house price gap due to the modelled collateral effects. This favourable demand shock stimulates output and reduces the unemployment gap, also driving up demand for credit by firms while inducing inflationary

³⁰The correlation is 0.56 for the monetary policy shocks and 0.87 for the housing demand shock, see Figure C.1 in Appendix C.

³¹Since the euro area interest rate series is proxied by the Shadow Short Rate, this shock captures the effects of both conventional and unconventional monetary policy.

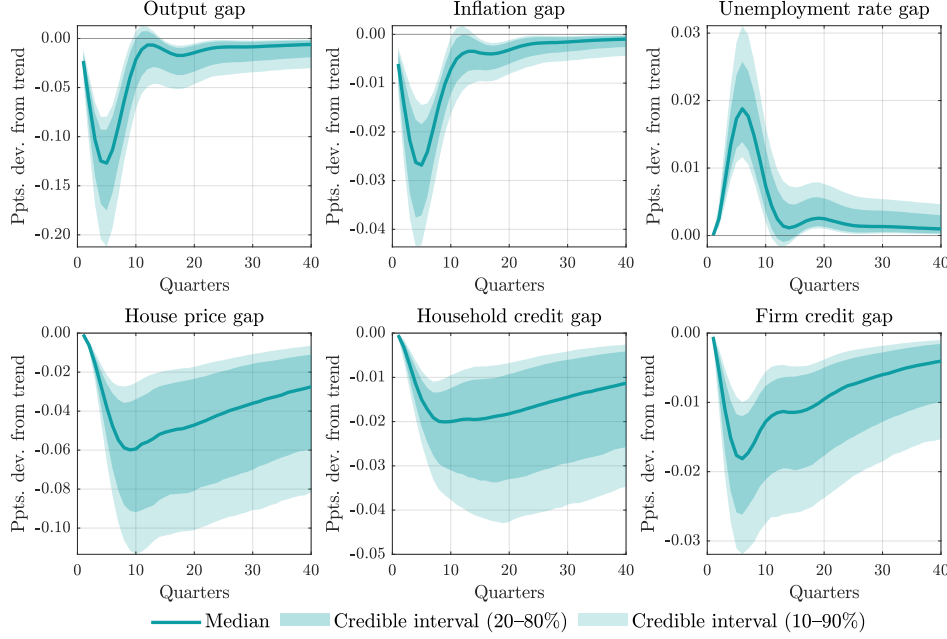


Figure 9: Impulse response functions to a euro area monetary policy shock

Notes: The figure shows the median response together with 60% and 80% credible bands, proxied by the 20th and 80th, and 10th and 90th percentiles, respectively. The asymmetry in some credible bands around the median reflect the shape of the posterior distributions of the model's estimated parameters.

pressures. The delayed and hump-shaped behaviour of credit is in line with the responses of a housing preference shock in an estimated DSGE model documented in [Iacoviello \(2015\)](#). These impulse response functions highlight the rich economic structure that is embedded in the model which disciplines the resulting credit gaps.

5.4 Early warning properties

The credit gap should ultimately be a measure of the build-up of cyclical risks which can potentially materialise in the real economy, either as a period of subdued economic activity due to deleveraging, or an outright recession brought on by a financial crisis. To this end, does the semi-structural credit gap built in this paper possess this early warning property? To answer this question, I follow [Lang et al. \(2019\)](#) and project future real GDP growth on the current values of the credit gap. Following [Jordà \(2005\)](#), I run local projections via the following set of regressions at horizons h :

$$y_{t+h} = \alpha + \beta_h x_{t-1} + \gamma_h z_t + \epsilon_t^h, \quad h = 0, 1, \dots, H \quad (44)$$

where y is an $n \times 1$ vector which includes real GDP growth and the semi-structural credit gap as endogenous variables, x is a vector of ρ lags of these endogenous variables, and z is a vector of controls, featuring the lags of euro area GDP growth and the shadow short rate. This system

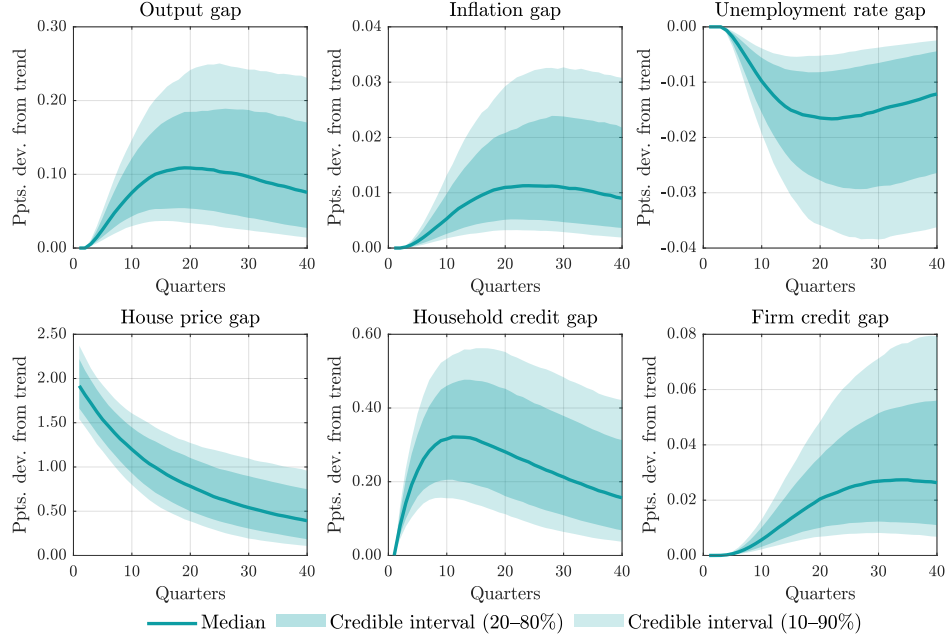


Figure 10: Impulse response functions to a housing demand shock

Notes: The figure shows the median response together with 60% and 80% credible bands, proxied by the 20th and 80th, and 10th and 90th percentiles, respectively. The asymmetry in some credible bands around the median reflect the shape of the posterior distributions of the model's estimated parameters.

directly yields the impulse response function (IRF) of real GDP growth to a rise in the credit gap – which is the object of interest – as the vector of relevant coefficients in the matrix β_h . I use observations for the period 2001Q1 up to 2019Q4, such that the estimates are not affected by the pandemic. I fix the lag of both endogenous and exogenous variables to 4; a reasonable lag window given the use of quarterly data, but a choice also dictated by the short span of the data. I limit the horizon H to 16 quarters for the same reason.

It is known that although VAR models and local projections estimate the same IRF *in population* as the lag length tends to infinity (Plagborg-Møller and Wolf, 2021), *sample* estimates from VAR models suffer from bias compared with those from local projections, but are more efficient (Li et al., 2022). This estimation uncertainty in local projections is likely more pronounced when the sample is very short, as in this application. To minimise this, I estimate (44) using a Bayesian approach akin to that proposed by Miranda-Agrippino and Ricco (2021) and Ferreira et al. (2023), termed Bayesian Local Projections. Although this approach favours implementing hierarchical priors using VAR estimates from a pre-sample, the length of the available data series does not allow for this. Instead, I impose a Normal-inverse Wishart prior on the system reflecting the belief that the variables follow a white noise process.³² This is a conjugate prior which centres the parameters around 0 with a unitary diagonal covariance matrix, and the residual covariance matrix as inverse Wishart with unitary diagonal elements

³²This is also the prior of choice of Ferreira et al. (2023) in the Monte Carlo exercises they run when they limit a working sample to only 80 observations, which is roughly the same number of observations of the credit gap available for this exercise.

as a scale matrix and $n + 1$ degrees of freedom. This choice follows a conservative view that the link between the credit gap and real GDP is weak at best but is only loosely imposed on the data.³³ The posterior distributions are then approximated using Gibbs sampling using the routines of [Canova and Ferroni \(2021\)](#).

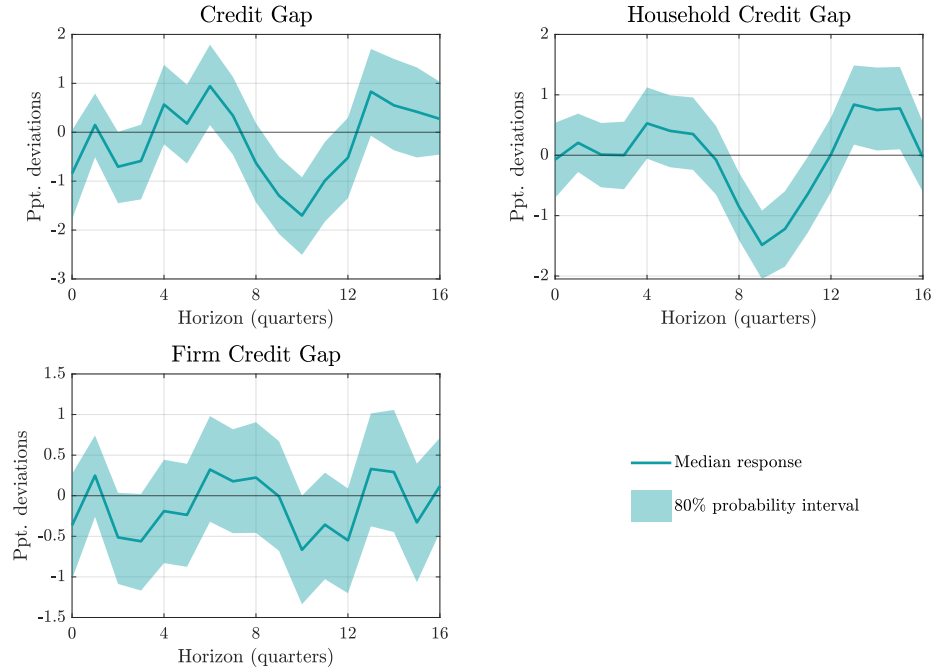


Figure 11: The dynamic response of real GDP growth to a 1 ppt. rise in the credit gap

Notes: The figure shows the median response surrounded by an 80% probability interval computed as the range between the 10th and the 90th percentiles of the responses based on 5,000 draws from the posterior distributions.

The top left panel in Figure 11 shows the response of yearly growth in real GDP at a horizon of up to four years following a 1 percentage point rise in the aggregate credit gap. The dynamic response is in line with the expected property of an early warning indicator; the effect of the build-up of risks is associated with an apparent rise in real GDP growth which is followed by an eventual slowdown, materializing only after at least two years.³⁴ The figure also shows the responses of real GDP to a 1 percentage point increase in both the household and the firm credit gaps. Evidently, the response based on the aggregate credit gap is derived exclusively from the household credit gap, which more clearly shows no effect on real GDP growth within the first year, followed by a rise and a subsequent decline. The response based on the firm credit gap, on the other hand, is erratic and does not deliver any clear story, and likely drives some of the volatility in the response based on the aggregate gap.

The finding that the boom-bust cycle is associated with household credit, and not with firm

³³The hyperparameter controlling the overall shrinkage is fixed at 1 at all horizons rather than set at the value that maximises the marginal likelihood at each horizon, given the short sample available.

³⁴The reversal in later quarters likely capture base effects, given that real GDP growth is in year-on-year terms.

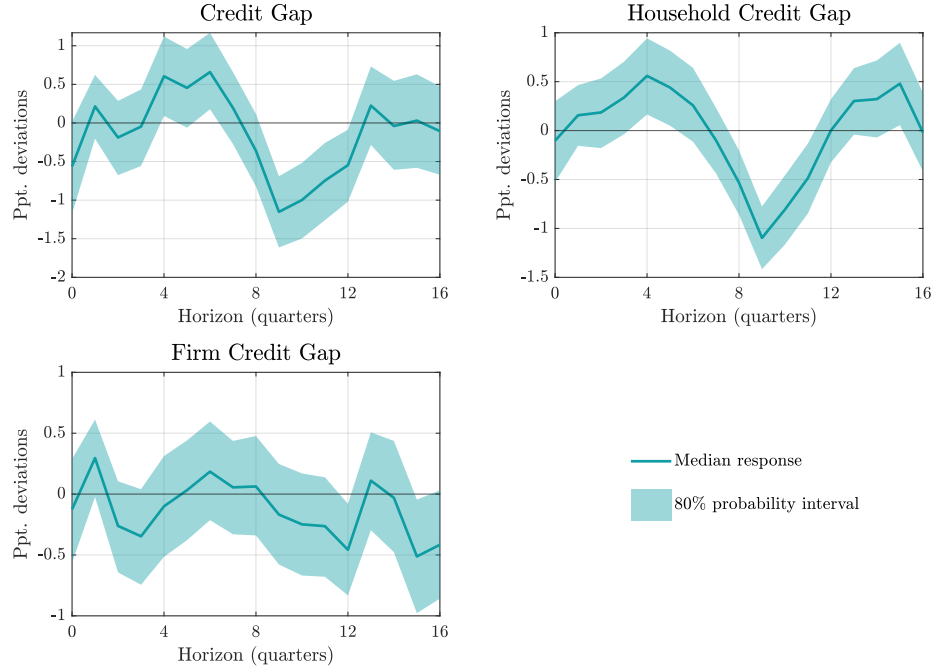


Figure 12: The dynamic response of the output gap to a 1 ppt. rise in the credit gap

Notes: The figure shows the median response surrounded by an 80% probability interval computed as the range between the 10th and the 90th percentiles of the responses based on 5,000 draws from the posterior distributions.

credit, is in line with the empirical results of [Mian et al. \(2017\)](#). As they discuss, these patterns are consistent with the collateral channel of house prices. Since housing constitutes a major share of household wealth, changes in house prices drive changes in net worth, with implications for credit and expenditure. On the other hand, firms likely use multiple forms of collateral (or rely on funding from mother companies) and hence their borrowing is less sensitive to house price movements and the financial cycle. Moreover, firms likely rely on favourable liquidity developments during booms, borrowing only during bad times. This reality also delinks the firm credit gap from the house price and household credit gaps, and correlates it negatively with economic activity. It can explain why most of the credible interval for real GDP growth in the bottom left panel of Figure 11 is in the negative range throughout the entire horizon.

A possible caveat with this analysis is the potential for spurious correlations driven by the fact that the credit gaps are based on the smoothed (two-sided) state estimates, especially for the results based on the output gap. To counter this, I re-estimate these local projections using the Kalman ‘updated’ (one-sided) estimates of credit gaps and the output gap. The results are reported in Appendix C and are qualitatively the same; the responses of real GDP and the output gap are positive at short horizons following an increase in the household credit gap, turning negative at longer horizons. The response in activity following a rise in the firm credit gap is similarly muted at most horizons, with a somewhat larger decline in the output gap at a horizon of 15 quarters. However, these IRFs are generally more noisy and are surrounded by a wider uncertainty. This is most likely because the one-sided estimates of the gaps are based

on a restricted information set relative to the two-sided estimates, thereby limiting their ability to appropriately characterize the state of the financial cycle. Therefore, the results presented in this section affirm the signalling properties of the credit gaps as derived from the multivariate filter.

6 Robustness

6.1 Benchmarking with other gaps

Latent variables are, by definition, unobservable. The multivariate filter used in this paper emphasises the role of economic theory to discipline the inferred trends and cycles, rather than imposing pure random walk assumptions for trends and auto-regressive or trigonometric processes for the cycles, as is typical in the literature. This should instil a level of confidence in the estimates presented in this paper. However, it is worth cross-checking them with estimates available from other sources. Figure 13 assesses the multivariate filter estimates of the output gap, NAIRU and the euro area output gap. The alternate Maltese output gap and NAIRU estimates are the official Central Bank of Malta estimates which are drawn from an unobserved components model based on a production function approach for potential output (‘UCM-PF’) (Ellul, 2019). This methodology is very similar to the one used in this paper but models potential output as a function of the economy’s labour, capital and total factor productivity, giving it a more structural process. The alternative output gap estimates for the euro area are those based on a similar unobserved component model (‘ECB-UCM’) based on the model by Tóth (2021) and estimates from Morley et al. (2023) using a Beveridge-Nelson decomposition. The multivariate filter estimates are well within the ballpark of the alternative estimates, although in the case of the NAIRU it is relatively more sensitive to economic developments, particularly during the COVID-19 pandemic.

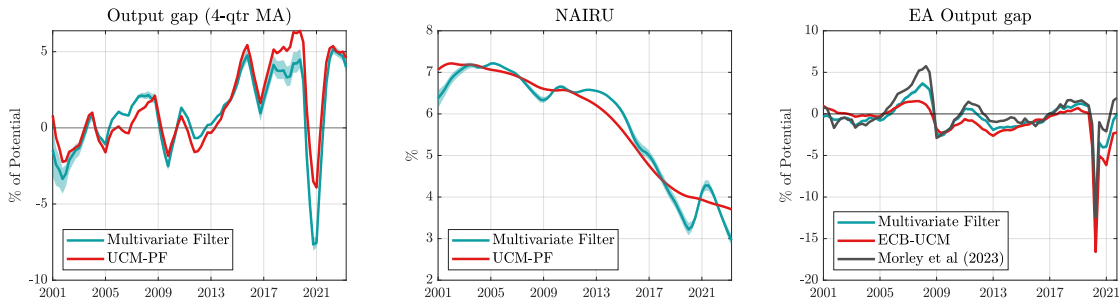


Figure 13: Benchmarking macroeconomic estimates with alternative sources

Notes: The figures show estimates from the multivariate filter (with the corresponding 80% probability interval), together with the Central Bank of Malta’s official estimates based on the model of Ellul (2019) (UCM-PF), and estimates for the euro area (EA) output gap based on the models of Tóth (2021) (ECB-UCM) and Morley et al. (2023). The output gaps for the Maltese economy are expressed in 4-quarter moving averages to smooth out inter-quarter volatility.

The semi-structural credit gap is an addition to the Central Bank of Malta’s cyclical analysis toolbox, complementing other summary indicators such as the Basel gap and the cyclical

Systemic Risk indicator (cSRI) (Vella, 2024).³⁵ Consequently, the Basel gap and the cSRI are, in principle, both complementary measures of the financial cycle. It is therefore instructive to compare the credit gap with these indicators to assess the extent to which they convey the same signal about the state of the financial cycle.

Figure 14 shows that the Basel gap for Malta somewhat agrees with the credit gap up to the first half of the sample period, identifying a negative gap in the period 2001-2007 which turns positive in the late 2000s (top left panel). The cSRI, which is only available from 2006, anticipates this increase a few years before, peaking in 2007-2008 (top right panel). However, the Basel gap turns negative again shortly after, reaching a trough of -30% by 2016, and remains negative through mid-2023. This leads to the conclusion that, according to this indicator, the potential accumulation of financial stability risks remains muted. This finding is at odds with the conclusions drawn from the semi-structural credit gap, which indicates rising risk starting from 2019 (mainly in the household sector, as discussed above), and therefore the need for corrective action.³⁶ On the other hand, the cSRI corroborates this narrative as it too turns positive in 2019 and keeps on rising until 2021.

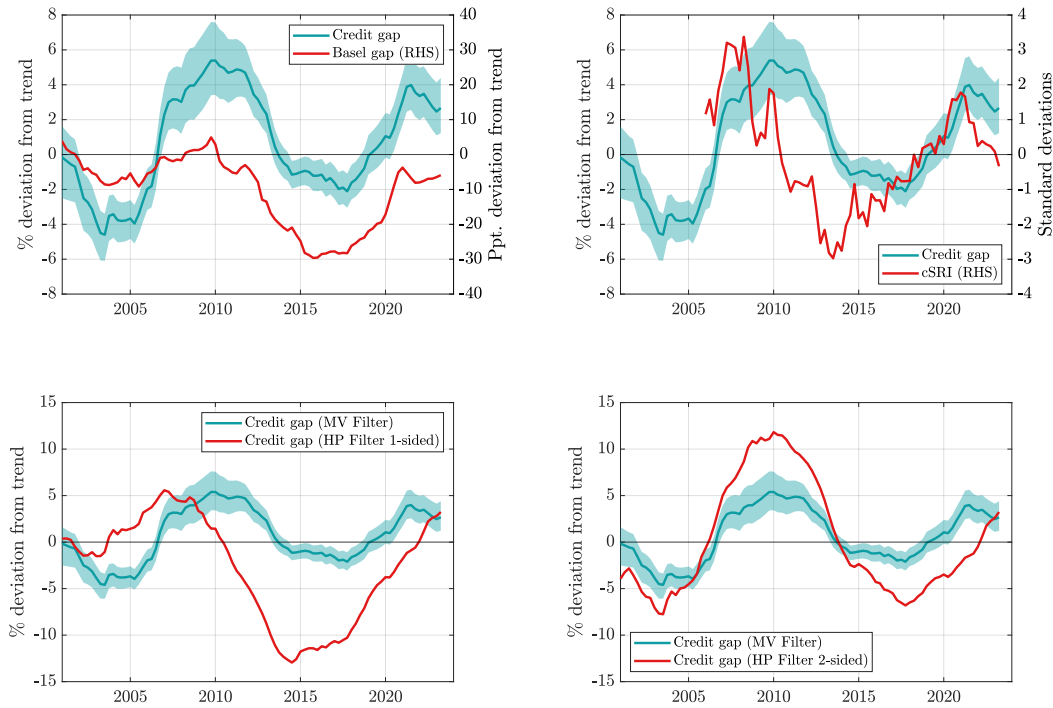


Figure 14: Measures of the financial cycle for Malta

Notes: The credit gap is surrounded by the 80% probability interval. See Central Bank of Malta (2023) for the Basel gap and Vella (2024) for the cSRI.

³⁵The cSRI is a composite indicator which captures the underlying movements in bank credit, the house price-to-income ratio, the debt service-to-income ratio and total debt relative to their long run behaviour.

³⁶The over-shooting property of the one-sided HP filter is the culprit for the Basel gap remaining persistently negative, since the credit-to-GDP ratio reached a peak of around 120% in 2010 and then fell to and stabilised around 75% from 2018 onwards, but the smooth one-sided HP filter takes a long time to ‘catch-up’

The cSRI is highly correlated with the household credit gap, both of which seem to lead the firm credit gap, at least in the sample period used in this study (see Figure C.4 in Appendix C). Since mid-2021 the cSRI experienced a turning point and started falling, turning negative. This is primarily due to the role of high inflation dampening developments in real credit and debt growth. In fact, a cSRI re-calculated using nominal data closely tracks the actual cSRI throughout the sample except for the last period, where it remains positive, in line with the signals derived from the aggregate and sectoral credit gaps. The semi-structural credit gap appears to be a more robust indicator in that it does not suffer from the over-shooting problem that plagues the Basel gap, similar to the credit gap derived in [Lang and Welz \(2018\)](#), and is not affected by periods of high or volatile inflation, as is the cSRI.³⁷ Figure 14 also shows the HP-filtered credit gaps based on the smoothing parameter used for the Basel gap. Both one-sided (left) and two-sided (right) underperform; the one-sided version exhibits the same over-shooting property, plunging the gap into deep negative territory in the mid-2010s. The two-sided version is more cyclical and correlates much better with the semi-structural credit gap, however towards the end of the sample it only flags a positive credit gap with a delay of several years, despite having the same information set as the semi-structural gap.

6.2 Revisions due to end-point bias

Smoothed (two-sided) state estimates are known to be subject to end-point bias and historical revisions. While this is an undesirable feature, [Benes et al. \(2010\)](#), [Andrle \(2013\)](#) and [Baba et al. \(2020\)](#) show that multivariate filters tend to suffer less from this property than other filters. To test the potential for revisions, I run a pseudo real time exercise in which I extract estimates of the output gap, the house price gap, and the household and firm credit gaps with different data vintages. The first vintage uses data up to 2015Q4, at which point the output gap was positive and at one of its recent historical highs. I repeat the process using data up to 2019Q4, which is the last period before the effects of pandemic start to show in the data. All the data used is the same apart from the different cut-off points, so this exercise controls for data revisions which are made in practice to National Accounts data. In a similar spirit, I do not re-estimate the model for each data vintage but use the same posterior distributions for the parameters and shock variances, such that exactly the same model is used across all the pseudo real-time decompositions. The sets of smoothed cycles are shown in Figure 15, together with the latest estimates for comparison.

While some cycles are revised over different data samples, the distributions across samples still largely overlap, such that the key findings remain unchanged. For instance, the mean house price gap turns positive in the 2015Q4 vintage, but is revised downwards as more data informs the decomposition. On the other hand, the mean house price gap as at 2019Q4 revises upwards with more data. Nevertheless, in both cases the 80% probability intervals overlap such that the real-time signal remains largely the same. A more noteworthy revision is that relating to the output gap and the firm credit gap as at 2019Q4, as subsequent information revises the output

³⁷The variables used to construct the cSRI are standardized, and during periods of high inflation the real growth of credit is more likely to be close to or below the long run average. This does not occur in the construction of the semi-structural credit gap.

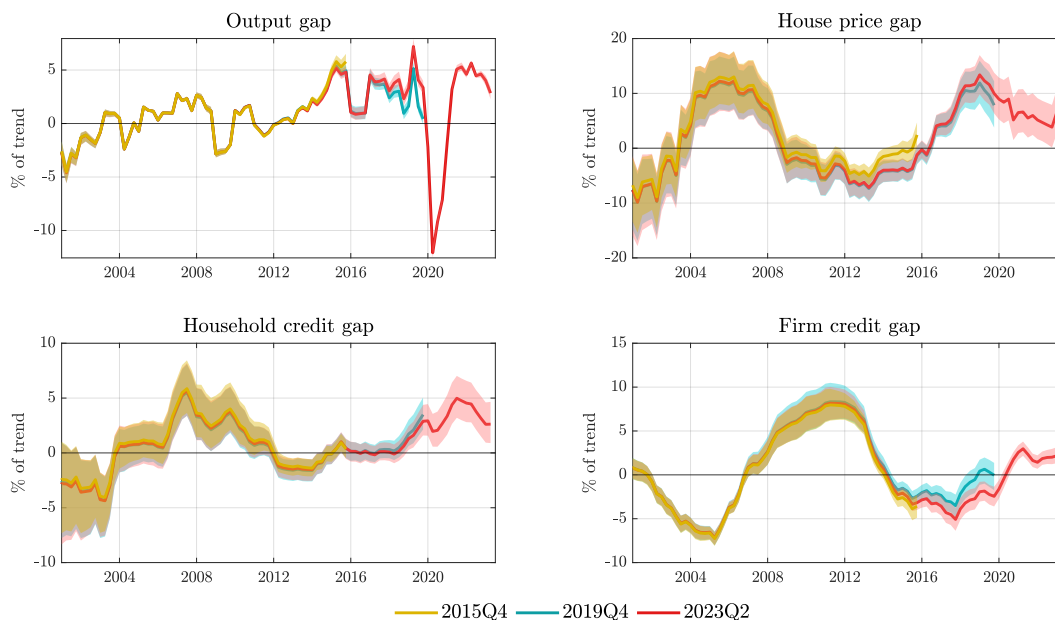


Figure 15: Gap estimates over different sample periods

Notes: The figure shows the smoothed cycles and the uncertainty around them, summarized by the range between the 10th and 90th percentiles, for a given data vintage. The date in the legend is the last observation used in each case to extract the cycles.

gap significantly up while it drags the firm credit gap down from around zero to a negative range. In the practical implementation of the multivariate filter, trends and cycles are likely to be revised due to data revisions and occasional re-estimation of the model's parameters and model re-specification. Despite this, the strength of using a two-sided filter is that it produces estimates of these latent variables using all available data, yielding the 'best guess' *for a given information set*. Therefore, revisions due to additional data points should not necessarily be viewed in a bad light, as they reflect difficulties in pinning down trends and cycles in real time which are inherent in any signal extraction problem. Indeed, the probability intervals that surround all the cycles presented in this paper partly reflect the uncertainty that surrounds any central estimate, and to an extent mitigate potential revisions by encompassing a range of outcomes rather than a single point.

6.3 The effect of the pandemic on the estimated gap

The estimated credit gap covers the period of the COVID-19 pandemic, which had a significant effect on the economy, seen most notably in GDP growth. Although the fiscal and macroprudential policies which were implemented in Malta limited the repercussions of this shock, it may still have led to a different evolution of the credit gap. This is especially the case if the gap is calculated not on the level of credit but on the credit-to-GDP ratio, in line with the methodology used to construct the Basel gap. This is because while credit levels remained stable or increased further, GDP collapsed during the pandemic, forcing the ratio to rise. Trend credit-to-GDP –

however measured – is unlikely to follow the same dynamics, causing the credit-to-GDP gap to widen and then contract once GDP recovers.

To study this, I estimate a Bayesian VAR (BVAR) on the same 11 variables with 6 lags, using the routines of [Canova and Ferroni \(2021\)](#). I use a Minnesota prior with the hyperparameter on overall tightness chosen such that it maximises the marginal data density, as discussed in [Canova \(2007\)](#) and [Giannone et al. \(2015\)](#).³⁸ I estimate the BVAR using data up to 2019Q4, and use the model to generate unconditional forecasts for all the endogenous variables for 2020Q1 to 2023Q2 using information available up to 2019Q4. These forecasts are shown in Figure C.5 in Appendix C, and represent reasonable counterfactual paths for the observables used in the multivariate filter from 2020 onwards in this scenario. In this counterfactual economic growth, house price growth and credit growth remain strong at close to average levels registered a few years before 2019. Although this story is plausible, it remains hypothetical, and any differences in the credit gap across scenarios is mainly illustrative rather than serving as an in-depth analysis of the pandemic and the effectiveness of any government policies.

The counterfactual credit gap is shown in Figure 16, with the benchmark credit gap included for comparison. Although the counterfactual gap follows a slightly different profile from 2020 onwards as it rises monotonically, the probability interval overlaps that of the benchmark estimate in several periods. The period in which the intervals overlap the least is in mid-2021, which is when the government imposed the second round of restrictions as measured by the Stringency index of the Oxford COVID-19 Government Response Tracker, see [Sant \(2021\)](#).³⁹ In fact, in this period potential output growth drops suddenly, dragging down the trend growth in house prices and credit to both sectors (see Figure 5). Through the lens of this alternative scenario the credit gap would have covered roughly the same range in terms of the probability distribution by mid-2023. A plausible interpretation is that the pandemic did not have long-lasting effects on the estimated trends in the model, such that roughly the same credit gap is observed by mid-2023 under both scenarios.

6.4 The credit gap vs. the credit-to-GDP gap

The Basel gap is computed using the credit-to-GDP ratio, such that developments in credit dynamics are studied relative to economic developments. In this section I calculate the credit-to-GDP gap using the measures of trend for both total credit and GDP (expressed as a four-quarter moving sum) from the multivariate filter and compare it with the Basel gap. The results are shown in the left panel of Figure 17. The credit-to-GDP gap based on the multivariate filter (teal shaded line) displays dynamics similar to the Basel gap up until 2010 but remains positive for longer, until 2013. It then turns negative and rises abruptly at the onset of the pandemic, a feature shared by the Basel gap to an extent. The credit-to-GDP gap then turns negative again

³⁸The implementation uses dummy observations to impose the prior, see [Canova and Ferroni \(2021\)](#) for more details. The overall tightness hyperparameter which maximises the marginal data density is 9.6135. The other hyperparameters are kept at values typically used in the literature; lag decay (0.5), Sum-of-Coefficients (5), co-persistence (2) and prior for the innovation covariance matrix (2).

³⁹A database with all the indicators updated up to December 2022 can be found here: <https://github.com/OxCGRT/covid-policy-dataset>.

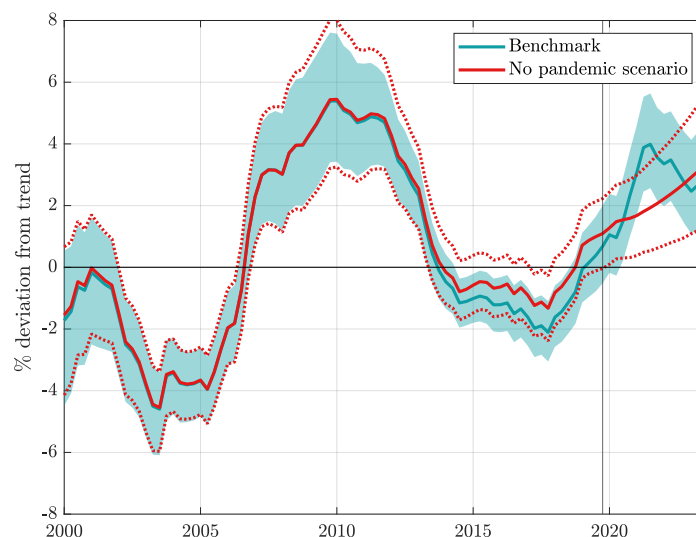


Figure 16: The effects of the COVID-19 pandemic on the credit gap

Notes: The figure shows the deviation of total nominal credit to households and firms from the inferred distribution of the economy-wide trend, in the benchmark case and in the counterfactual scenario of no pandemic. The probability bands are formed using the 10th and 90th percentiles. The solid vertical line denotes 2019Q4, the last period for which the data over the two scenarios are the same.

as from end-2021. This is the only period in which it conveys a signal which is different from that obtained from the credit gap, shown for reference in the same panel.

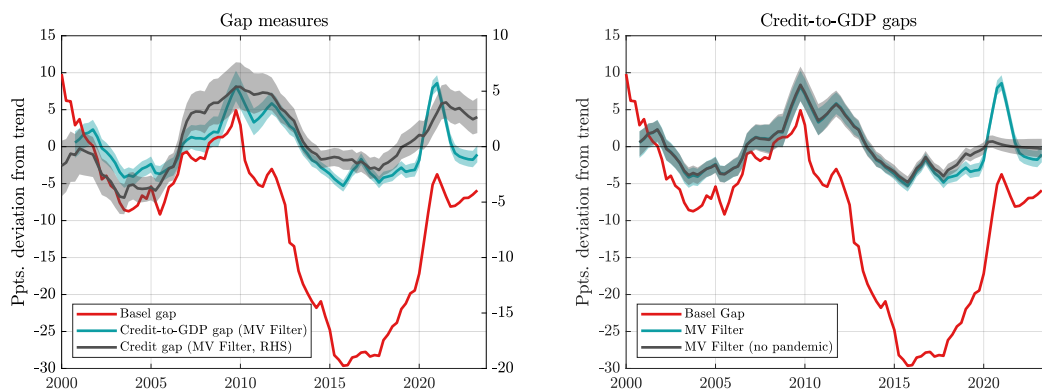


Figure 17: The credit-to-GDP gap

Notes: The credit-to-GDP gap from the Multivariate Filter starts from 2000Q4 due to the use of a four-quarter moving sum for GDP. ‘MV’ denotes multivariate filter.

The reason for this divergence is the path of output growth after the pandemic, which remained high by historical standards, causing the credit-to-GDP ratio to fall.⁴⁰ Even though

⁴⁰In fact, the ratio was at a 20-year low of 71.5% by the end of 2019, but it jumped to around 82% at the height of the pandemic and then fell back to less than 74% by early 2023.

the trend credit-to-GDP ratio implied by the multivariate filter is relatively more volatile than that implied by the HP filter as applied for the Basel gap, it still does not adjust quickly enough to these fluctuations in the data. This explains the negative credit-to-GDP gap as from end-2021. Indeed, the panel on the right in Figure 17 shows the gap which would result in the counterfactual scenario of no pandemic studied above (grey shaded line). In this case the credit-to-GDP gap remains virtually flat at 2019 levels.⁴¹

7 Policy implications and conclusion

Macroprudential policymakers face several challenges in the conduct of their mandate. They observe data with a lag, which they then need to analyse and assess with respect to macroeconomic and financial theory and a thorough understanding of an economy’s functioning. They then face a dilemma related to the need to act and, if warranted, deliberate on the timing of such implementation. The credit gap constructed in this paper goes some way towards addressing these challenges in Malta. First, by filtering credit developments through a semi-structural macroeconomic model, it yields economically meaningful measures of trends, against which the data is assessed. This is in contrast with univariate approaches which are largely void of any economic institution. Second, by presenting a *distribution* of outcomes for the state of the financial cycle, it paradoxically reduces the uncertainty around the need for action, as the probability of the credit gap exceeding any given threshold can be readily evaluated and used to inform judgement. This is in line with recent advances in policymaking which link financial conditions with future tail risk events (IMF, 2017; Adrian et al., 2019; Lang et al., 2023). Third, an additional useful feature of the model is its ability to decompose the aggregate credit gap by sectors, since it allows sectoral credit gaps and trends to be driven by idiosyncratic factors. This can therefore be used to study whether rises in risk are broad-based or sector-specific, thereby guiding policymakers on the appropriate macroprudential policy response using the most suitable tool.

One of the findings documented in this paper is that the house price gap leads the household credit gap, a pattern which is not readily visible in the raw data. This intertemporal link is important as it confirms the central role that housing plays as collateral for household credit in Malta. Household credit, in turn, is shown to have signalling properties such that a positive gap, proxying a rise in sectoral cyclical risks, is associated with a boom-bust cycle in GDP growth and the output gap. Therefore, the house price gap in itself can be a useful reference and predictor of the expected state of the financial cycle with a lead of 2–3 years.

Another policy-relevant issue worth discussing is the reality that indicators, irrespective of how they are derived, are likely to indicate false positives from time to time, and indicators derived using different approaches are also occasionally likely to disagree about the signal (Drehmann and Yetman, 2021). Indicators are also potentially subject to revisions as more data becomes available or as some data is revised. Although these sources of uncertainty are a fact of life in real-time analysis, the semi-structural credit gap derived in this paper does not appear to be prone to strong real-time backward revisions, as shown in Section 6. Additionally, even if the

⁴¹See Figure C.6 in Appendix C for the data and trends relating to the credit-to-GDP ratio in the benchmark and counterfactual scenarios, respectively.

gap is somewhat revised, the probability distributions of different credit gap vintages are likely to largely overlap, such that the main signal remains unchanged. Ultimately, macroprudential policy formulation does not only rely on indicators but also requires expert judgement, and a very careful consideration of the balance between the costs of acting early and the costs of inaction.

References

- Adjemian, S., Bastani, H., Juillard, M., Karamé, F., Mihoubi, F., Mutschler, W., Pfeifer, J., Ratto, M., Rion, N., and Villemot, S. (2024). Dynare: Reference Manual, Version 6. Dynare Working Papers 80, CEPREMAP.
- Adolfson, M., Laséen, S., Christiano, L., Trabandt, M., and Walentin, K. (2013). Ramses II – Model description. *Sveriges Riksbank Occasional Paper Series 12*.
- Adrian, T., Boyarchenko, N., and Giannone, D. (2019). Vulnerable growth. *American Economic Review*, 109(4):1263–1289.
- Alessandri, P., Bologna, P., Fiori, R., and Sette, E. (2015). A note on the implementation of a countercyclical capital buffer in Italy. *Banca d’Italia Occasional Paper Series*, (278).
- Alessandri, P., Bologna, P., and Galardo, M. (2022). Financial crises, macroprudential policy and the reliability of credit-to-GDP gaps. *IMF Economic Review*, 70(4):625–667.
- Andrle, M. (2013). What is in your output gap? Unified framework & decomposition into observables. *Working Paper no. 105/13, International Monetary Fund*.
- Apel, M. and Jansson, P. (1999). System estimates of potential output and the NAIRU. *Empirical economics*, 24:373–388.
- Baba, C., Dell’Erba, S., Detragiache, E., Harrison, O., Mineshima, A., Musayev, A., and Shahmoradi, A. (2020). How should credit gaps be measured? An application to European countries. *Working Paper no. 20/6, International Monetary Fund*.
- Basel Committee (2010). Guidance for national authorities operating the countercyclical capital buffer. *Basel Switzerland*.
- Behn, M., Detken, C., Peltonen, T. A., and Schudel, W. (2013). Setting countercyclical capital buffers based on Early Warning Models: Would it work? *Working paper no. 1604, European Central Bank*.
- Benes, J., Clinton, K., Garcia-Saltos, R., Johnson, M., Laxton, D., Manchev, P., and Matheson, T. (2010). Estimating potential output with a multivariate filter. *Working Paper no. 10/285, International Monetary Fund*.

- Benes, J. and N'Diaye, P. M. (2004). A multivariate filter for measuring potential output and the NAIRU: Application to the Czech Republic. *Working Paper no. 04/45, International Monetary Fund*.
- Blaggrave, P., Garcia-Saltos, R., Laxton, D., and Zhang, F. (2015). A simple multivariate filter for estimating potential output. *Working Paper no. 15/79, International Monetary Fund*.
- Borio, C. and Lowe, P. (2002). Assessing the risk of banking crises. *BIS Quarterly Review*, 7(1):43–54.
- Butler, L. (1996). *A semi-structural method to estimate potential output: Combining economic theory with a time-series filter*.
- Canova, F. (2007). *Methods for Applied Macroeconomic Research*. Princeton University Press.
- Canova, F. and Ferroni, F. (2021). A Hitchhiker’s Guide to Empirical Macro Models. *Working Paper no. WP-2021-15, Federal Reserve Bank of Chicago*.
- Carabenciov, I., Ermolaev, I., Freedman, C., Juillard, M., Kamenik, O., Korshunov, D., and Laxton, D. (2008). A Small Quarterly Projection Model of the US Economy. *Working Paper no. 08/278, International Monetary Fund*.
- Carvalho, A. (2023). The euro area natural interest rate – Estimation and importance for monetary policy. *Banco de Portugal Economic Studies*, IX.
- Central Bank of Malta (2018). Box 3: A review of the corporate bond market in Malta. In *Financial Stability Report 2017*, pages 29–33.
- Central Bank of Malta (2023). The Countercyclical Capital Buffer Rate. Financial Stability Department, December 2023.
- Coenen, G., Karadi, P., Schmidt, S., and Warne, A. (2018). The New Area-Wide Model II: an extended version of the ECB’s micro-founded model for forecasting and policy analysis with a financial sector. *Working Paper 2200, European Central Bank*.
- Darmanin, J. (2017). The financing of companies in Malta. *Policy Note, Central Bank of Malta*, July 2017.
- Dell’Ariccia, G., Igan, D., Laeven, L., Tong, H., Bakker, B., and Vandebussche, J. (2014). Policies for macrofinancial stability: How to deal with credit booms. In Claessens, S., Kose, M. A., Laeven, L., and Valencia, F., editors, *Financial Crises – Causes, Consequences and Policy Responses*, pages 325–364. International Monetary Fund.
- Detken, C., Weeken, O., Alessi, L., Bonfim, D., Boucinha, M., Castro, C., Frontczak, S., Giordana, G., Giese, J., Jahn, N., Kakes, J., Klaus, B., Lang, J. H., Puzanova, N., and Welz, P. (2014). Operationalising the countercyclical capital buffer: indicator selection, threshold identification and calibration options. *ESRB: Occasional Paper Series*, (2014/5).
- Drehmann, M., Borio, C. E., Gambacorta, L., Jimenez, G., and Trucharte, C. (2010). Countercyclical capital buffers: exploring options. *BIS Working Paper no. 317*.

- Drehmann, M. and Yetman, J. (2018). Why you should use the Hodrick-Prescott filter—at least to generate credit gaps. *BIS Working Paper no. 744*.
- Drehmann, M. and Yetman, J. (2021). Which credit gap is better at predicting financial crises? A comparison of univariate filters. *International Journal of Central Banking*, 17(4):225–255.
- Ellul, R. (2019). Box 1: An unobserved components model for potential output in Malta. In *Quarterly Review 2019:2*, pages 19–21.
- Fabiani, S. and Mestre, R. (2004). A system approach for measuring the euro area NAIRU. *Empirical Economics*, 29:311–341.
- Ferreira, L. N., Miranda-Agrippino, S., and Ricco, G. (2023). Bayesian local projections. *The Review of Economics and Statistics*, In Press.
- Galati, G., Hindrayanto, I., Koopman, S. J., and Vlekke, M. (2016). Measuring financial cycles in a model-based analysis: Empirical evidence for the United States and the euro area. *Economics Letters*, 145:83–87.
- Gatt, W. (2022). MEDSEA-FIN: An estimated DSGE model with housing and financial frictions for Malta. *Working Paper no. 05/2020, Central Bank of Malta*.
- Gatt, W. (2024). Loan-to-value limits as a macroprudential policy tool: Developments in theory and practice. *Journal of Economic Surveys*, 38(1):232–267.
- Gatt, W. and Grech, O. (2016). An assessment of the Maltese housing market. *Policy Note, Central Bank of Malta*, September 2016.
- Giannone, D., Lenza, M., and Primiceri, G. E. (2015). Prior selection for vector autoregressions. *Review of Economics and Statistics*, 97(2):436–451.
- Greenwood, R., Hanson, S. G., Shleifer, A., and Sørensen, J. A. (2022). Predictable financial crises. *The Journal of Finance*, 77(2):863–921.
- Guillochon, J. and Le Roux, J. (2023). Unobserved components model(s): output gaps and financial cycles. *Working Paper no. 2832, European Central Bank*.
- Hamilton, J. D. (2018). Why you should never use the Hodrick-Prescott filter. *Review of Economics and Statistics*, 100(5):831–843.
- Hamilton, J. D. and Leff, D. (2020). Measuring the credit gap. *Unpublished mimeo*.
- Harvey, A. and Koopman, S. (1997). Multivariate Structural Time Series Models. In *Systematic Dynamics in Economic and Financial Models*, pages 269–298. John Wiley & Sons.
- Hasenzagl, T., Pellegrino, F., Reichlin, L., and Ricco, G. (2023). Monitoring the economy in real time: Trends and gaps in real activity and prices. *CREST Working Paper no. 6*.
- Holston, K., Laubach, T., and Williams, J. C. (2017). Measuring the natural rate of interest: International trends and determinants. *Journal of International Economics*, 108:S59–S75.

- Iacoviello, M. (2005). House prices, borrowing constraints, and monetary policy in the business cycle. *American Economic Review*, pages 739–764.
- Iacoviello, M. (2015). Financial business cycles. *Review of Economic Dynamics*, 18(1):140–163.
- Igan, D. O., Kabundi, A. N., De Simone, F. d. N., Pinheiro, M., and Tamirisa, N. T. (2009). Three cycles: Housing, credit, and real activity. *IMF Working Paper no. 231*.
- IMF (2017). Financial conditions and growth at risk. In *Global Financial Stability Report: Is Growth at Risk?* International Monetary Fund, Washington, DC.
- Iskrev, N. (2010). Local identification in DSGE models. *Journal of Monetary Economics*, 57(2):189–202.
- Jarociński, M. and Lenza, M. (2018). An inflation-predicting measure of the output gap in the euro area. *Journal of Money, Credit and Banking*, 50(6):1189–1224.
- Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182.
- Karagedikli, Ö. and Rummel, O. J. (2020). Weighing up the Credit-to-GDP gap: A cautionary note. *MAGKS Joint Discussion Paper Series in Economics*, 22-2020.
- Karam, P., Pranovich, M., and Vlcek, J. (2021). An extended Quarterly Projection Model: Credit cycle, macrofinancial linkages and macroprudential measures: The case of the Philippines. *Working Paper no. 21/256, International Monetary Fund*.
- Krippner, L. (2013). Measuring the stance of monetary policy in zero lower bound environments. *Economics Letters*, 118:135–138.
- Krippner, L. (2020). Documentation for shadow short rate estimates. www.ljkmfa.com.
- Krznar, I. and Matheson, T. (2017). Financial and business cycles in Brazil. *Working Paper no. 17/12, International Monetary Fund*.
- Kuttner, K. N. (1991). Using noisy indicators to measure potential output. *Working Paper no. 14, Federal Reserve Bank of Chicago*.
- Kuttner, K. N. (1994). Estimating potential output as a latent variable. *Journal of Business & Economic Statistics*, 12(3):361–368.
- Lang, J. H., Izzo, C., Fahr, S., and Ruzicka, J. (2019). Anticipating the bust: A new cyclical systemic risk indicator to assess the likelihood and severity of financial crises. *ECB Occasional Paper*, 219.
- Lang, J. H., Rusnák, M., and Greiwe, M. (2023). Medium-term growth-at-risk in the euro area. *ECB Working Paper no. 2808*.
- Lang, J. H. and Welz, P. (2017). Measuring credit gaps for macroprudential policy. In *Financial Stability Review 2017*. European Central Bank.

- Lang, J. H. and Welz, P. (2018). Semi-structural credit gap estimation. *Working Paper no. 2194, European Central Bank*.
- Laubach, T. and Williams, J. C. (2003). Measuring the natural rate of interest. *Review of Economics and Statistics*, 85(4):1063–1070.
- Laxton, D., Kostanyan, A., Liqokeli, A., Minasyan, G., Nurbekyan, A., and Sopromadze, T. (2019). Mind the gaps! Financial-cycle output gaps and monetary-policy-relevant output gaps. *London School of Economics and Political Science Working Paper*.
- Laxton, D. and Tetlow, R. (1992). A simple multivariate filter for the measurement of potential output. *Bank of Canada Technical Report No. 59*.
- Li, D., Plagborg-Møller, M., and Wolf, C. K. (2022). Local projections vs. VARs: Lessons from thousands of DGPs. *NBER Working Paper no. 30207*.
- Lo Duca, M., Koban, A., Basten, M., Bengtsson, E., Klaus, B., Kusmierczyk, P., Lang, J. H., Detken, C., and Peltonen, T. (2017). A new database for financial crises in European countries. *ECB Occasional Paper*, (2017/194). (Updated December 2021).
- Lubik, T. A., Matthes, C., et al. (2015). Calculating the natural rate of interest: A comparison of two alternative approaches. *Richmond Fed Economic Brief*, (October).
- Mian, A., Sufi, A., and Verner, E. (2017). Household debt and business cycles worldwide. *The Quarterly Journal of Economics*, 132(4):1755–1817.
- Micallef, B. (2016). A multivariate filter to estimate potential output and NAIRU for the Maltese economy. *International Journal of Economics and Finance*, 8(5):13–22.
- Miranda-Agrippino, S. and Ricco, G. (2021). The transmission of monetary policy shocks. *American Economic Journal: Macroeconomics*, 13(3):74–107.
- Morley, J., Rodríguez-Palenzuela, D., Sun, Y., and Wong, B. (2023). Estimating the euro area output gap using multivariate information and addressing the COVID-19 pandemic. *European Economic Review*, 153:104385.
- Neal, R. M. (2003). Slice sampling. *The Annals of Statistics*, 31(3):705–767.
- Plagborg-Møller, M. and Wolf, C. K. (2021). Local projections and VARs estimate the same impulse responses. *Econometrica*, 89(2):955–980.
- Planas, C., Ratto, M., and Rossi, A. (2015). Slice sampling in Bayesian estimation of DSGE models. *Unpublished mimeo*.
- Repullo, R. and Saurina, J. (2011). The countercyclical capital buffer of Basel III: A critical assessment. *CEMFI Working Paper no. 1102*.
- Rünstler, G. and Vlekke, M. (2018). Business, housing, and credit cycles. *Journal of Applied Econometrics*, 33(2):212–226.

- Sant, K. (2021). The COVID-19 pandemic and disruption in 2020: Developing a Government Response Tracker for Malta. *Policy Note, Central Bank of Malta*, April 2021.
- Schmitt-Grohé, S. and Uribe, M. (2012). What’s news in business cycles. *Econometrica*, 80(6):2733–2764.
- Schularick, M. and Taylor, A. M. (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870–2008. *American Economic Review*, 102(2):1029–1061.
- Schüler, Y. S. (2020). On the credit-to-GDP gap and spurious medium-term cycles. *Economics Letters*, 192:109245.
- Schüler, Y. S., Hiebert, P., and Peltonen, T. A. (2015). Characterising the financial cycle: a multivariate and time-varying approach. *Working Paper no. 1846, European Central Bank*.
- Strohsal, T., Proaño, C. R., and Wolters, J. (2019). Characterizing the financial cycle: Evidence from a frequency domain analysis. *Journal of Banking & Finance*, 106:568–591.
- Tóth, M. (2021). A multivariate unobserved components model to estimate potential output in the euro area: A production function based approach. *Working Paper no. 2523, European Central Bank*.
- Vella, S. (2024). Constructing a cyclical Systemic Risk indicator for Malta. *Working Paper no. 01/2024, Central Bank of Malta*.

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.

GDP

Real GDP for Malta and the euro area are defined as the chain-linked 2015 volumes, and relate to the 2032Q2 data vintage and are subject to revisions. I seasonally adjust real GDP for Malta using X-13, and express both real GDP series in logarithms. I use the unadjusted nominal and real GDP for Malta to construct the GDP deflator, used below.

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

Unemployment rate

The unemployment rate is based on the Labour Force Survey, and is sourced from Eurostat. I seasonally adjust it using X-13.

- Unemployment rate: `Eurostat/lfsq_urgan/Q.PC.T.Y15-64.TOTAL.MT`.

HICP inflation

I use the HICP index sourced from Eurostat and take quarterly averages, and calculate inflation rates using year-on-year percentage changes.

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

House prices

House prices are sourced from the Central Bank of Malta's house price index, which is based on advertised property prices. The index is rebased to 100 in 2000 and deflated using the HICP.

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. I 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 macroeconomic model, and splicing the missing values for OMFI loans back to 2000Q1 based on quarterly growth rates. I then deflate household credit using the HICP.

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. I 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 splicing the missing values for OMFI loans back to 2000Q1 based on quarterly growth rates. I deflate credit to firms using the GDP deflator for Malta.

Interest rates for households and firms

I build the lending interest rates for households and firms by splicing MIR interest rates (new business), available from January 2008 onwards, with the OMFI lending rates to households and firms for the earlier period, using the spread between these series between 2008 and 2021. All data is sourced from the Central Bank of Malta and I take quarterly averages.

ECB policy rate

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

Appendix B Parameters

B.1 Calibrated shocks

Table B.1 summarizes the calibration of the variances of shocks and measurement errors.

B.2 Priors and posteriors

The priors on the parameters follow the convention in the literature; I use Inverse Gamma distributions for shock variances, Beta distributions for parameters bound between 0 and 1 and Gamma distributions for all other parameters which govern the dynamics. The priors are neither loose nor overly tight and reflect beliefs over the relative size and effect of the semi-structural relationships embedded in the model. For instance, most gaps and the growth rate of trends are *a priori* believed to be highly persistent at a quarterly frequency, so the priors over their AR(1) coefficient are centred around 0.8. Other priors for parameters which do not have a clear structural interpretation are set around values which delivered sensible dynamics to a euro area interest rate shock or sensible inference of trends and cycles in preliminary testing. The posterior distributions for several parameters are informed by the data such that they are either more tightly concentrated around the prior mode or have mass over a different support. Some other parameters are poorly identified and in this case the prior plays a dominant role in representing the uncertainty around a parameter. Tables B.2 – B.3 and Figures B.1–B.3 summarize the prior and posterior distributions.

Table B.1: Calibrated shocks

Parameter	Std. dev.	Comment
Shocks		
$\nu^{\overline{Y}}$	0.04	Potential output level
ν^{gY}	0.08	Potential output growth
$\nu^{\overline{U}}$	0.01	NAIRU level
$\nu^{\overline{P_h}}$	1.20	Trend house price level
ν^{gP_h}	0.75	Trend house price growth
$\nu^{\overline{C_h}}$	0.10	Trend household credit level
ν^{gC_h}	0.25	Trend household credit growth
$\nu^{\overline{C_f}}$	0.12	Trend firm credit level
ν^{gC_f}	0.25	Trend firm credit growth
$\nu^{\overline{R_h}}$	0.05	Trend household interest rate
$\nu^{\overline{R_f}}$	0.05	Trend firm interest rate
$\nu^{\overline{Y}^*}$	0.20	EA Potential output level
$\nu^{g\overline{Y}^*}$	0.05	EA Potential output growth
$\nu^{\overline{y}^*}$	1.00	EA output gap
$\nu^{\overline{\pi}^*}$	0.12	EA Trend inflation
$\nu^{\overline{R}^*}$	0.20	EA trend interest rate
Measurement errors		
ε^Y	0.25	Output
ε^U	0.15	Unemployment
ε^{P_h}	1.10	House prices
ε^{C_h}	0.40	Household credit
ε^{C_f}	1.20	Firm credit

Table B.2: Prior and posterior distributions - dynamics

Parameter	Prior			Posterior			
	Distribution	Mean	Std. dev.	Mean	10 th	Median	90 th
θ_1^Y	Gamma	0.600	0.050	0.842	0.766	0.841	0.921
θ_2^Y	Gamma	0.100	0.050	0.094	0.042	0.087	0.157
θ_4^Y	Gamma	0.100	0.050	0.083	0.036	0.076	0.138
θ_5^Y	Gamma	0.100	0.050	0.072	0.033	0.067	0.118
τ^Y	Beta	0.800	0.100	0.990	0.989	0.990	0.990
ρ^Y	Beta	0.800	0.100	0.800	0.683	0.810	0.905
ρ_1^π	Beta	0.800	0.100	0.916	0.871	0.928	0.947
ρ_2^π	Beta	0.800	0.100	0.811	0.697	0.819	0.915
θ_1^π	Gamma	0.120	0.050	0.126	0.066	0.119	0.195
θ_2^π	Gamma	0.170	0.050	0.174	0.113	0.170	0.242
θ_3^π	Gamma	0.150	0.050	0.163	0.098	0.157	0.237
θ_1^U	Gamma	0.030	0.005	0.011	0.009	0.011	0.013
θ_2^U	Gamma	0.150	0.010	0.110	0.101	0.110	0.119
ρ^U	Beta	0.800	0.100	0.265	0.174	0.257	0.368
$\theta_1^{P_h}$	Gamma	0.100	0.050	0.134	0.081	0.133	0.188
$\theta_2^{P_h}$	Gamma	0.100	0.050	0.093	0.042	0.086	0.153
ρ^{P_h}	Beta	0.800	0.100	0.944	0.909	0.948	0.973
$\theta_1^{C_h}$	Gamma	0.100	0.050	0.090	0.047	0.088	0.136
$\theta_3^{C_h}$	Gamma	0.050	0.025	0.045	0.022	0.043	0.069
$\theta_4^{C_h}$	Gamma	0.050	0.030	0.038	0.014	0.034	0.069
$\theta_5^{C_h}$	Gamma	0.500	0.100	0.281	0.220	0.279	0.346
τ^{C_h}	Beta	0.800	0.100	0.985	0.981	0.985	0.988
ρ^{C_h}	Beta	0.800	0.050	0.839	0.780	0.842	0.894
$\theta_1^{C_f}$	Gamma	0.100	0.050	0.044	0.020	0.040	0.073
$\theta_3^{C_f}$	Gamma	0.050	0.030	0.045	0.015	0.039	0.081
$\theta_4^{C_f}$	Gamma	0.500	0.100	0.370	0.286	0.367	0.458
τ^{C_f}	Beta	0.800	0.100	0.929	0.863	0.946	0.976
ρ^{C_f}	Beta	0.800	0.050	0.907	0.873	0.910	0.937
$\rho_1^{R_h}$	Beta	0.500	0.100	0.558	0.451	0.558	0.666
$\rho_2^{R_h}$	Beta	0.500	0.050	0.632	0.572	0.634	0.690
$\theta_1^{R_h}$	Beta	0.600	0.100	0.244	0.214	0.244	0.276
$\rho_1^{R_f}$	Beta	0.500	0.100	0.478	0.355	0.477	0.602
$\rho_2^{R_f}$	Beta	0.500	0.050	0.523	0.464	0.524	0.582
$\theta_1^{R_f}$	Beta	0.600	0.100	0.369	0.330	0.368	0.408

Notes: Posterior distributions are based on 4,000 retained draws from each of 10 chains. The marginal posterior distribution for each variable is summarised by the mean, median and the 10th and 90th percentile.

Table B.3: Prior and posterior distributions - shocks

Shock	Prior			Posterior			
	Distribution	Mean	Std. dev.	Mean	10 th	Median	90 th
$\nu^{\tilde{y}}$	Inv. Gamma	3.500	0.100	3.363	3.246	3.361	3.481
$\nu^{\tilde{\pi}}$	Inv. Gamma	0.250	0.075	0.386	0.241	0.371	0.552
$\nu^{\tilde{\pi}}$	Inv. Gamma	0.700	0.050	0.709	0.654	0.707	0.766
$\nu^{\tilde{u}}$	Inv. Gamma	0.050	0.001	0.051	0.049	0.051	0.052
$\nu^{\tilde{p}_h}$	Inv. Gamma	0.250	0.100	1.952	1.558	1.941	2.359
$\nu^{\tilde{c}_h}$	Inv. Gamma	1.000	0.100	0.878	0.798	0.875	0.963
$\nu^{\tilde{r}_h}$	Inv. Gamma	0.100	0.050	0.176	0.149	0.175	0.204
$\nu^{\tilde{c}_f}$	Inv. Gamma	1.000	0.100	1.152	1.015	1.145	1.298
$\nu^{\tilde{r}_f}$	Inv. Gamma	0.100	0.050	0.323	0.283	0.321	0.364
ν^{r*}	Inv. Gamma	0.100	0.050	0.668	0.579	0.663	0.762

Notes: Posterior distributions are based on 4,000 retained draws from each of 10 chains. The marginal posterior distribution for each variable is summarised by the mean, median and the 10th and 90th percentile.

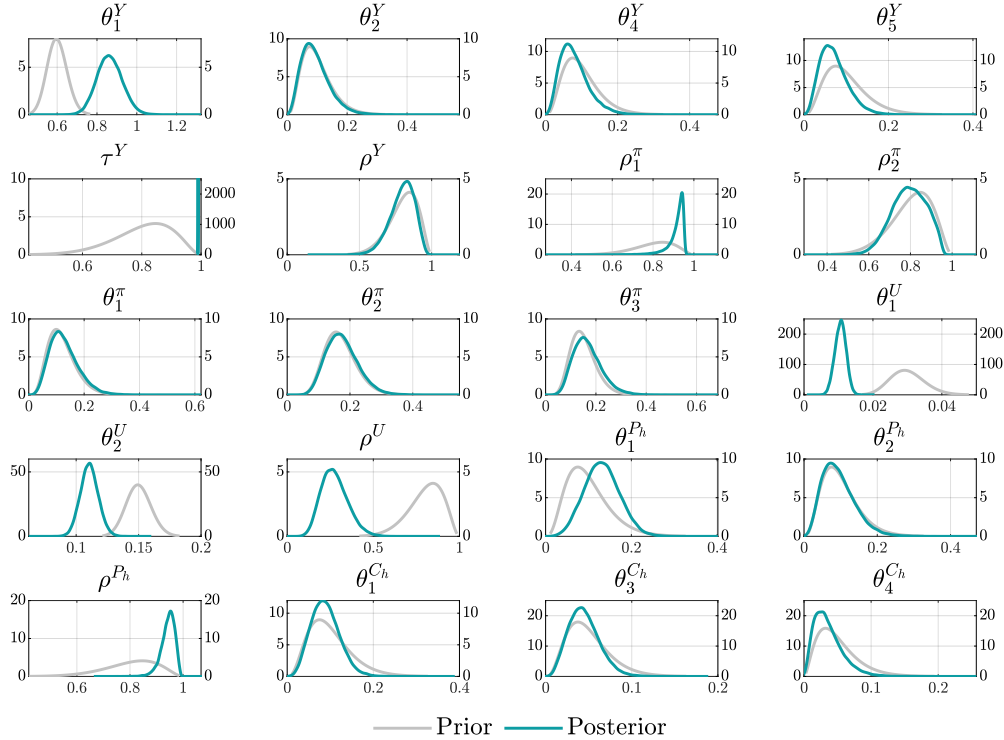


Figure B.1: Prior and posterior distributions (dynamics)

Notes: Posterior distributions are based on 4,000 retained draws from each of 10 chains. In the subplot for τ^Y the prior is plotted on the left y-axis while the posterior is on the right.

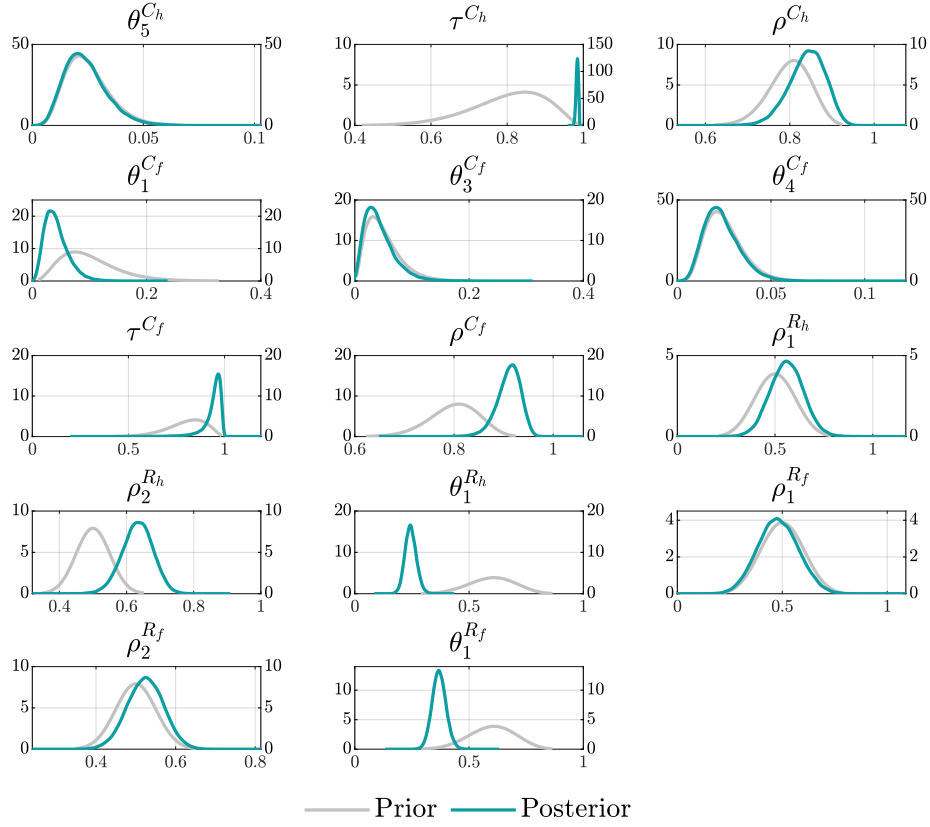


Figure B.2: Prior and posterior distributions (dynamics, cont.)

Notes: Posterior distributions are based on 4,000 retained draws from each of 10 chains. In the subplot for τ^{C_h} the prior is plotted on the left y-axis while the posterior is on the right.

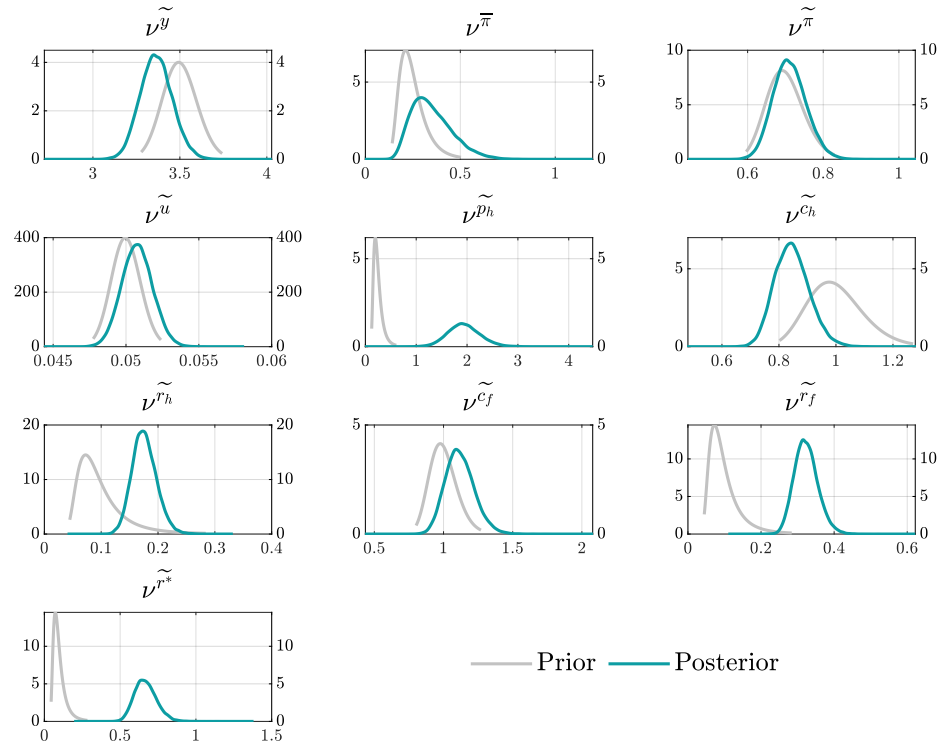


Figure B.3: Prior and posterior distributions (shocks)

Note: Posterior distributions are based on 4,000 retained draws from each of 10 chains.

Appendix C Other figures

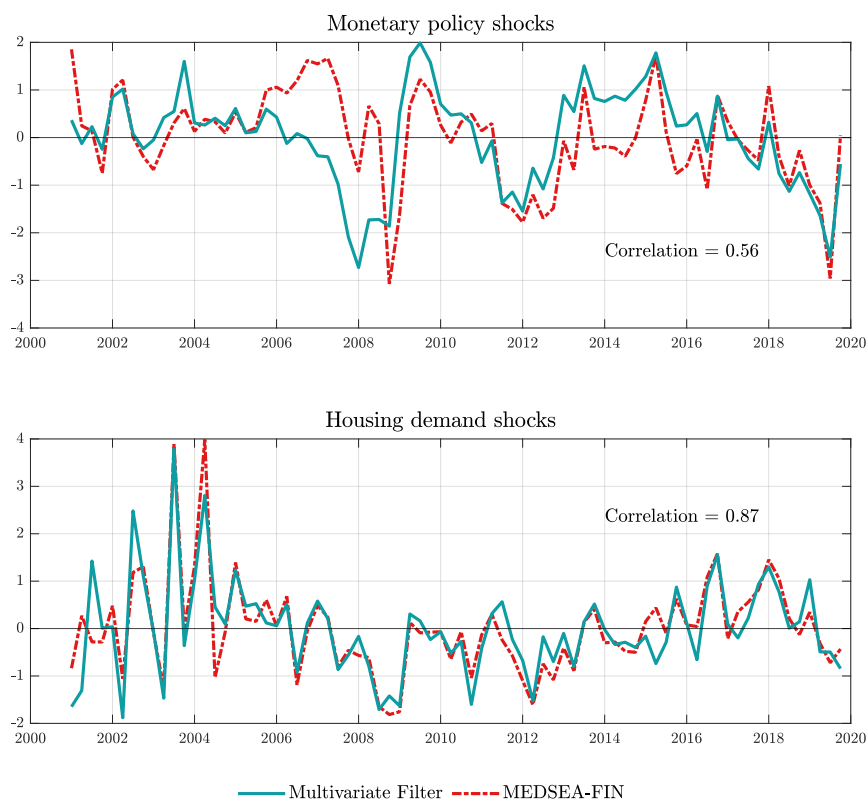


Figure C.1: Shocks across models

Note: The figure shows the mean shock series across models, both standardized. See [Gatt \(2022\)](#) for details on the estimation of MEDSEA-FIN.

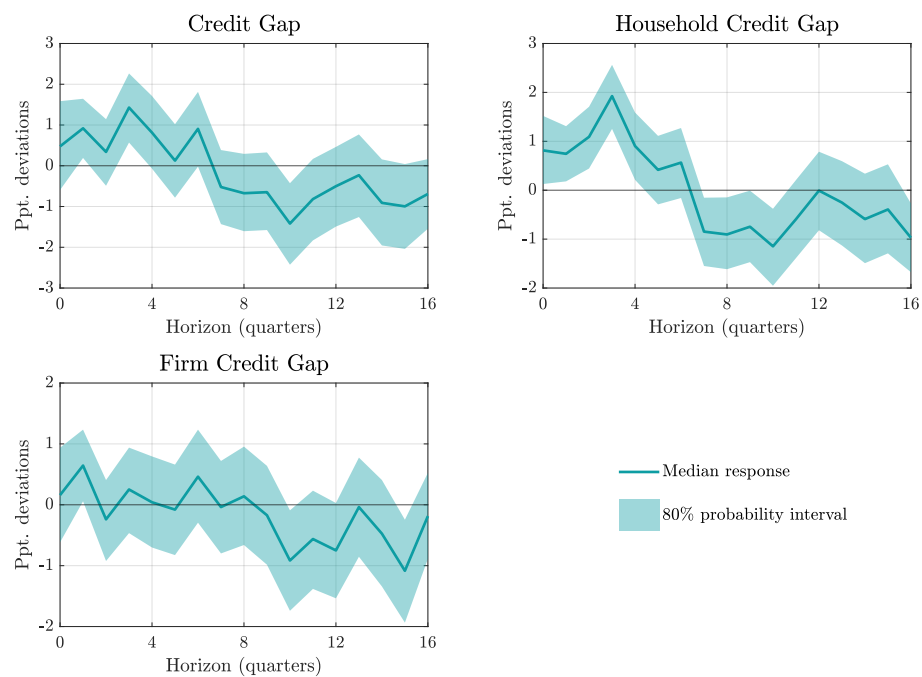


Figure C.2: The dynamic response of real GDP growth to a 1 ppt. rise in the credit gap (updated states)

Notes: The figure shows the median response surrounded by an 80% probability interval computed as the range between the 10th and the 90th percentiles of the responses based on 5,000 draws from the posterior distributions. Results are based on the updated rather than the smoothed state estimates.

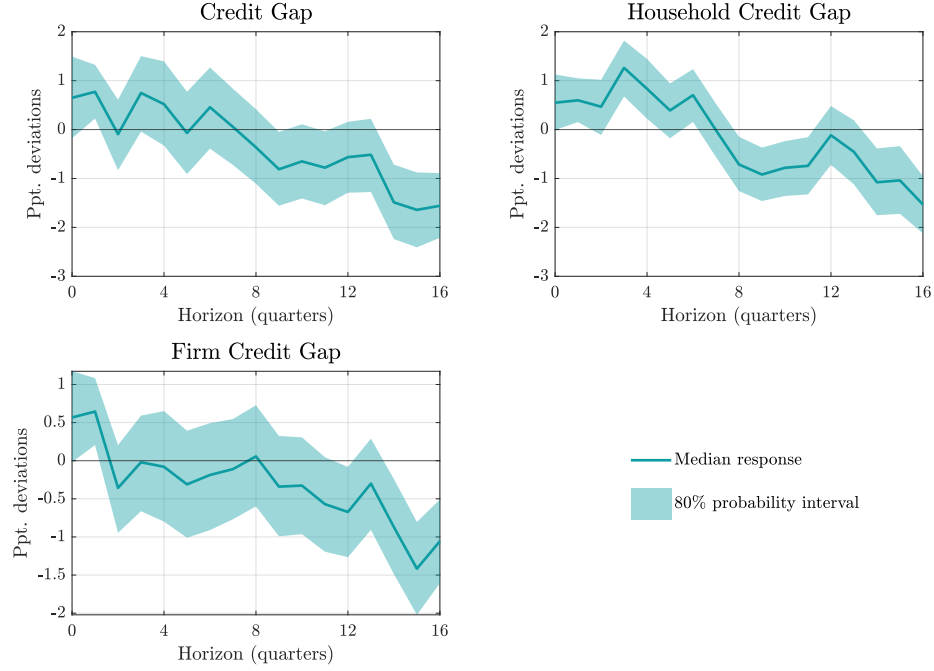


Figure C.3: The dynamic response of the output gap to a 1 ppt. rise in the credit gap (updated states)

Notes: The figure shows the median response surrounded by an 80% probability interval computed as the range between the 10th and the 90th percentiles of the responses based on 5,000 draws from the posterior distributions. Results are based on the updated rather than the smoothed state estimates.

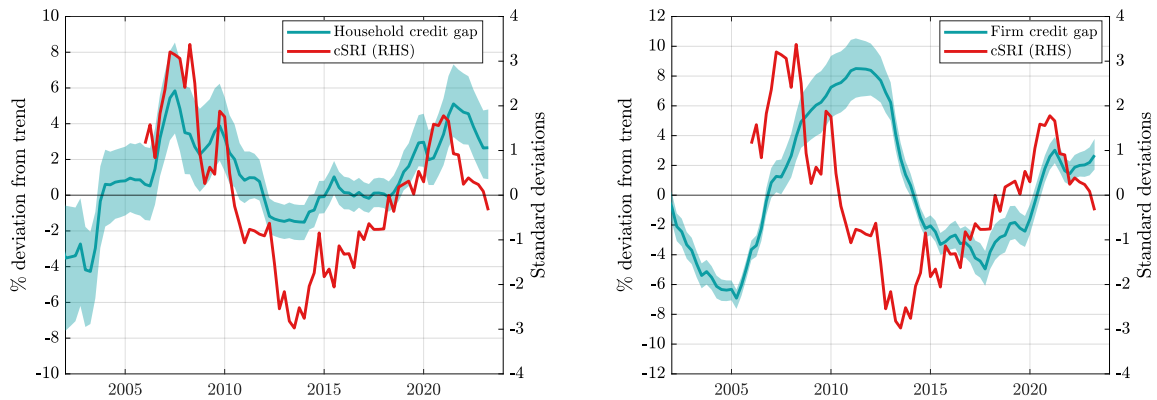


Figure C.4: The cSRI and sectoral credit gaps

Notes: The credit gaps are surrounded by the 80% probability interval. See [Vella \(2024\)](#) for the cSRI.

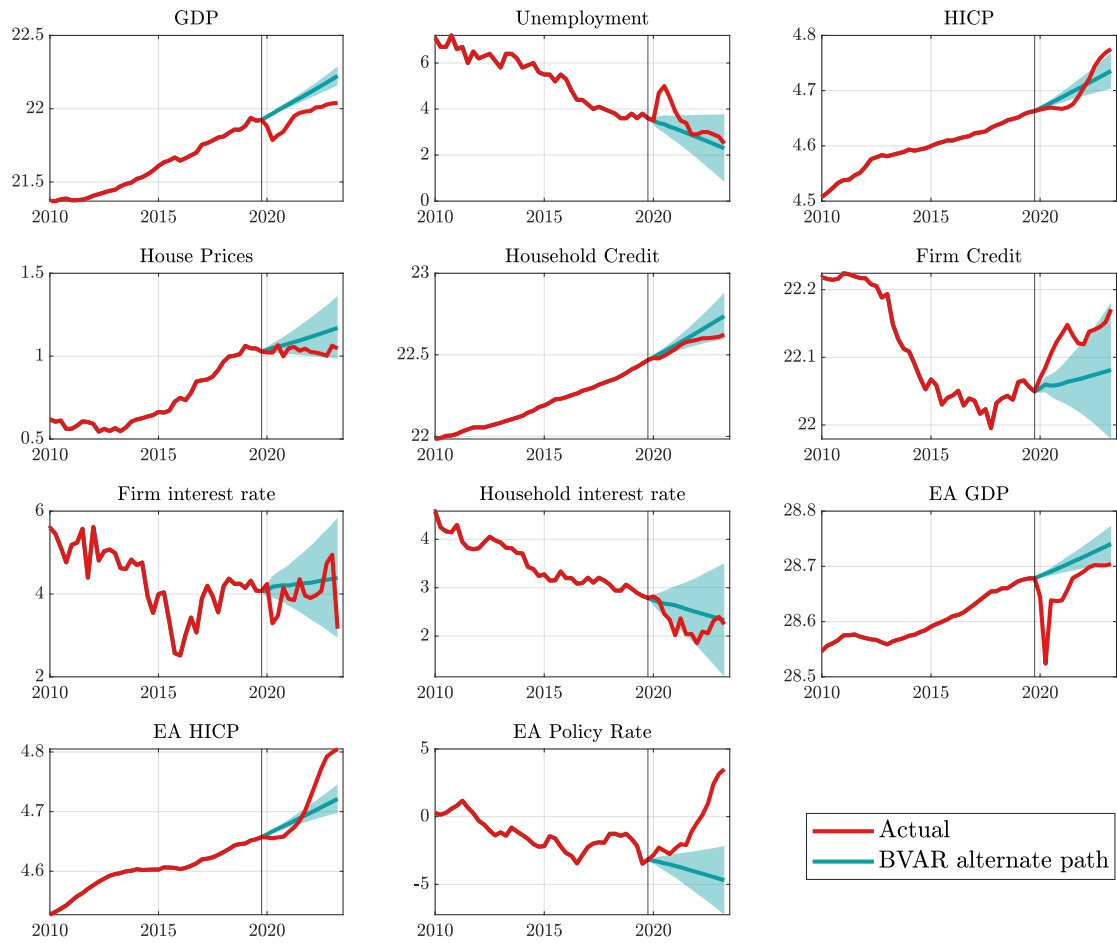


Figure C.5: BVAR alternate paths

Notes: Actual data and alternative paths generated by a BVAR, summarized via the mean and 80% credible intervals. The vertical solid line denotes the last datapoint used to estimate the BVAR (2019Q4).

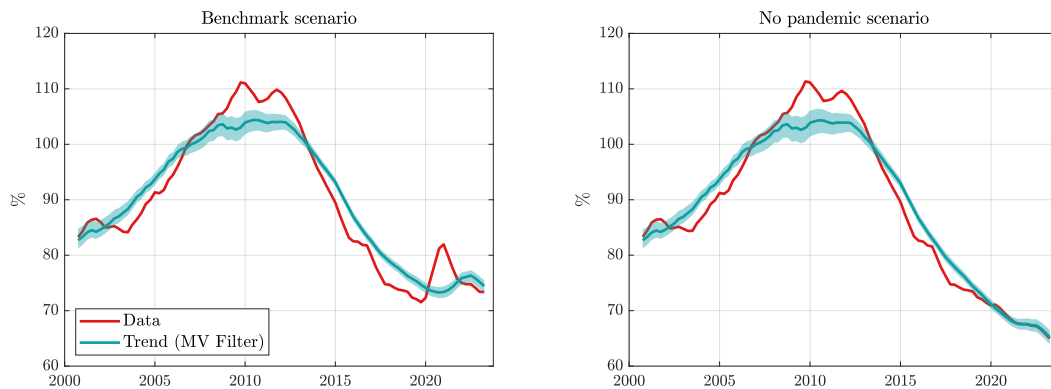


Figure C.6: The credit-to-GDP ratio and trends across scenarios

Notes: The credit-to-GDP gap from the multivariate filter starts from 2000Q4 due to the use of a four-quarter moving average for GDP.