SPECIAL FEATURE: A MEASURE OF THE CREDIT GAP FOR MALTA[1]

Policymakers observe data about the economy, sometimes with considerable lags, and analyse that data to infer whether any corrective policy action is required. This data, in its raw form, may not always give clear signals on whether any policy intervention is called for. To this end, policymakers employ an array of analytical tools, from simple data transformations to complex modelling. In the case of macroprudential policy, one such tool of analysis is the Basel gap, which measures the deviation of a country's aggregate credit to GDP ratio from its trend, to gauge the likelihood of excessive borrowing and risk-taking. The Basel Committee on Banking Supervision established the use of the 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 (Basel Committee, 2010).[2] This gap is a proxy for the financial cycle, which is what policymakers aim to track. The trend used in this calculation is unobserved and is therefore estimated using a one-sided Hodrick Prescott (HP) filter, calibrated to deliver a very smooth trend.[3] This method is statistical in nature but incorporates economists' views that the underlying financial cycle is three to four times longer than business cycles. Drehmann et al. (2010) and more recently Drehmann and Yetman (2018) document that this indicator can perform well in the prediction of systemic banking crises relative to other univariate approaches.[4]

However, the Basel gap is not without its shortcomings. 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.[5] This potentially amplifies rather than dampens the pro-cyclicality between downturns and risk. 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).[6] This leads to large and persistent negative gaps for several countries, including Malta, and limits its use. In Malta this effect is caused by the financial liberalisation which took place in the 1990s, which led to strong credit growth relative to GDP, causing the credit-to-GDP ratio to rise significantly. 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.

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.[7] 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.[8] Nevertheless, other methods to uncover the financial cycle are being studied at the Central Bank of Malta.[9]

This article presents estimates of a semi-structural credit gap which is derived using a multivariate filter.[10] Like the HP filter, this methodology decomposes observed data into (unobserved) trend and cycle components.

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[2] Basel Committee (2010). Guidance for national authorities operating the countercyclical capital buffer. Basel, Switzerland.

[3] This decision follows the analysis of several indicators by Drehmann, M., Borio, C. E., Gambacorta, L., Jimenez, G., and Trucharte, C. (2010). Countercyclical capital buffers: exploring options. BIS Working paper no. 317, who find that this indicator outperforms other measures, such as credit growth, asset price growth and banking sector profits and losses.

[4] Drehmann, M., Borio, C., Gambacorta, L., Jiménez, G. and Trucharte, C. (2010). Countercyclical capital buffers; exploring options. *BIS Working Paper No. 317*., and Drehmann, M., and Yetman, J. Why you should use the Hodrick-Prescott filter — at least to generate credit gaps. 2018. *BIS Working Paper no. 744.*

[5] See Repullo, R. and Saurina, J. (2011). The countercyclical capital buffer of Basel III: A critical assessment. *CEMFI Working Paper No. 1102.*

[6] Lang, J. H. and Welz, P. (2017). Special Feature B: Measuring credit gaps for macroprudential policy, in *Financial Stability Review*, May 2017, European Central Bank.

[7] 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. See Basel Committee (2010). Guidance for national authorities operating the countercyclical capital buffer, Basel, Switzerland, p. 3.

[8] These assessments can be viewed on the Central Bank of Malta website.

[9] See Vella, S. (2023). Box 1: A cyclical Systemic Risk Indicator for Malta, in *Financial Stability Report 2022,* Central Bank of Malta.

[10] More technical details will be published in Gatt, W. (forthcoming), A semi-structural credit gap for Malta: A multivariate filter approach, *Central Bank of Malta Working Paper.*

However, it is considerably more flexible and allows for the joint determination of trends and cycles of many variables simultaneously. More importantly, it also allows for the incorporation of economic relationships among unobserved variables, which can discipline the estimates relative to statistical filters, such that it allows for a better narrative. The model includes several Maltese macroeconomic variables, namely real GDP, the unemployment rate, inflation, real house prices, real bank credit to households, real bank credit to firms, the respective interest rates on household and firm credit, as well as euro area real GDP, euro area inflation and a proxy for the ECB's monetary policy stance.[11] The multivariate filter posits the following system of equations for each variable in the model as follows:

$$X_t = \overline{X}_t + \tilde{x}_t + \nu_t \quad (1)$$

$$\overline{X}_t = \overline{X}_{t-1} + g_t^{\overline{X}} + [other\ terms] + \epsilon_t^{\overline{X}} \quad (2)$$

$$g_t^{\overline{X}} = \tau g_{t-1}^{\overline{X}} + (1-\tau)g + \epsilon_t^{g} \quad (3)$$

$$\tilde{x}_t = \rho\tilde{x}_{t-1} + [other\ terms] + \epsilon_t^{\tilde{x}} \quad (4)$$

Equation (1) defines the observed variable X_t as the sum of a trend $\overline{X}_t$ and a cycle $\tilde{x}_t$ component, as well as measurement error ν_t. This measurement error picks up volatility in the data which the model does not attribute to either the trend or the cycle. Equation (2) states how the trend component evolves over time, such that its one period change is a function of a time-varying growth rate $g_t^{\overline{X}}$ as well as other terms. These other terms could be movements in the estimated trend or cycle of another variable in the model. This time-varying growth rate is assumed to be a persistent autoregressive process of order 1 (AR(1)) around a long-run fixed growth rate g in equation (3).[12] Finally, equation (4) states that the cycle $\tilde{x}_t$ is also modelled as AR(1) process, but additionally can be driven by developments in trends or cycles of other variables in the model. The trend, its growth rate and cycle can be hit by random disturbances $\epsilon_t^{\overline{X}}$, ϵ_t^{g} and $\epsilon_t^{\tilde{x}}$, respectively. A strength of this approach is that credit gaps are informed by developments across the macroeconomy, which can improve their usefulness compared to univariate approaches.[13] For instance, the trend and cycle for real household credit are also a function of developments of the trend and cycle in real house prices, capturing a collateral channel, as well as developments in potential output, the output gap, the trend and the cycle of the household interest rate, capturing demand factors. Similar demand determinants are present in the trend and cycle for real credit to firms. The resulting cycles represent the credit gaps in the household and corporate sectors, respectively and are aggregated to form the economy-wide semi-structural credit gap.

The parameters of the model as well as the variances of the disturbances are calibrated or estimated using Bayesian techniques, using data spanning the period 2000Q1 to 2019Q4. Given a set of parameters, the model is used to derive the estimates of the underlying trend and cycle components using all available data via the Kalman filter. A key advantage of using a Bayesian framework is that the results are derived in terms of a probability distribution, which reflect the inherent uncertainty in these latent variables.

[11] House prices and household credit are deflated using the HICP, while firm credit is deflated using the GDP deflator.

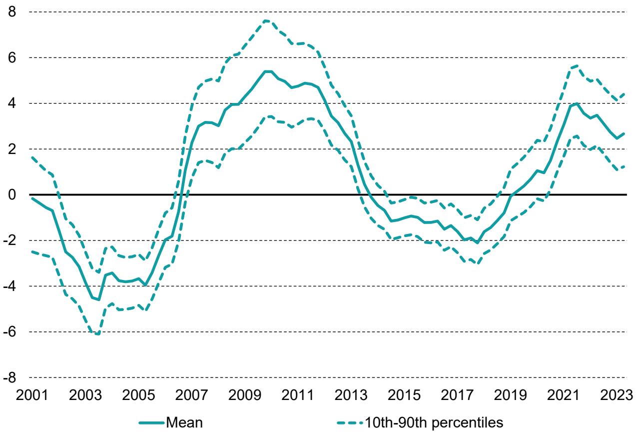
[12] The system of equations for stationary variables such as the unemployment rate, inflation rates and interest rates does not include this equation, and the trend equation follows an AR(1) process instead of a random walk with drift.

[13] See Behn, M., Detken, C., Peltonen, T. A., and Schudel, W. (2013). Setting countercyclical capital buffers based on Early Warning Models: Would it work? *ECB Working Paper No. 1604*, 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*, *No. 2014/5*, and 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*, Vol.17, No.4, pp. 225-255.

The semi-structural credit gap

Chart 1 shows the distribution of the estimated credit gap for Malta from 2001Q1 to 2023Q2 using the multivariate filter approach. The semi-structural credit gap is defined such that a gap of say 2% implies that the actual level of credit outstanding is 2% above the estimated trend.[14] The credit gap is cyclical, with an average duration of 13 years per cycle, which is in line with the literature on financial cycles.[15] 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 up until 2023Q2.

Chart 1
THE CREDIT GAP
(% of trend)

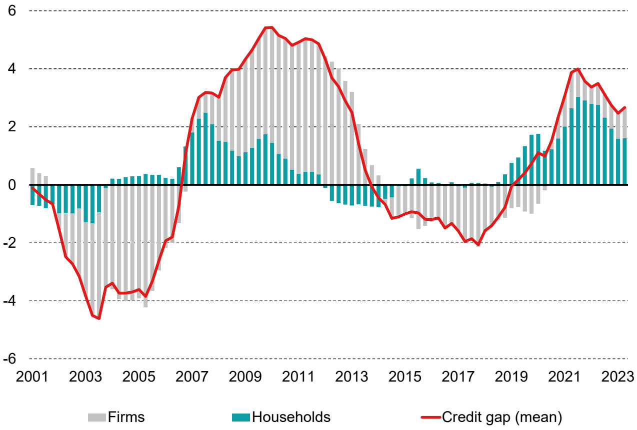


Source: Author's estimates.

The chart also shows the uncertainty around the mean credit gap estimate, proxied by the 10th and 90th percentiles of the underlying distribution, which is a commonly used measure of uncertainty. The latter reflects 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. This allows for a probabilistic assessment of the credit gap. For example, the model estimates an 80% probability that the gap was between 1.2% and 4.4% in 2023Q2, with a mean estimate of 2.7%. This conveys a clear signal that the gap was well within the positive range, with credit being above fundamentals. 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 is 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.

The model can also be used to investigate the dynamics of sectoral credit gaps and assess their contribution to the aggregate gap. Chart 2 decomposes the credit gap shown in Chart 1 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

Chart 2
SECTORAL DECOMPOSITION OF THE CREDIT GAP
(% of trend)



Source: Author's estimates.

[14] Note that the semi-structural credit gap is defined relative to the trend level of credit, not trend level of credit-to-GDP. This helps to remove the potential for the gap to be affected neither by the effects of financial liberalisation nor the strong growth in GDP, as discussed above.

[15] See, for instance, Lang, J. H. and Welz, P. (2018). Semi-structural credit gap estimation. *ECB Working Paper No. 2194*, and Strohsal, T., Proaño, C. R., and Wolters, J. (2019). Characterizing the financial cycle: Evidence from a frequency domain analysis. *Journal of Banking & Finance*, Vol. 106, pp. 568-591.

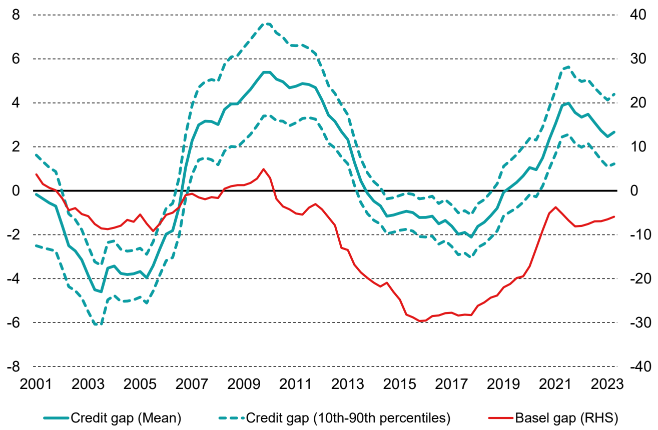
factors. First, the share of loans to firms represented the bulk of loans issued, representing more than 70% of total bank lending in the early 2000s. This ratio fell progressively over the sample period, as growth in household mortgages outstripped growth in loans to firms, reaching 50% by mid-2013, 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. The model's ability to decompose the aggregate credit gap by sectors is a very useful feature, as it can indicate whether rises in risk are broad-based or sector-specific, thereby guiding policymakers on the appropriate macroprudential policy response.

Benchmarking with existing indicators

The semi-structural credit gap is an addition to the Central Bank of Malta's cyclical analysis toolbox, complementing other indicators such as the Basel gap and the cyclical systemic risk indicator (cSRI), amongst others.[16] The 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. It is instructive to compare the credit gap with both indicators to assess the likelihood that they convey the same signal. Chart 3 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. However, it 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. The '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'.

Chart 3
THE CREDIT GAP AND THE BASEL GAP
(% of trend)



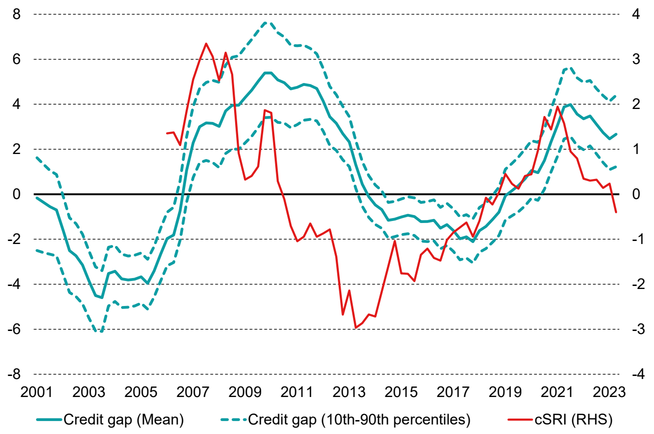
Sources: Author's estimates and Central Bank of Malta.

Turning to the other key indicator, Chart 4 shows that the cSRI is more likely to flag turning points in the financial cycle that line up with or even anticipate those identified by the semi-structural credit gap. Indeed, the cSRI correlates well

[16] See Central Bank of Malta (2023). *The Countercyclical Capital Buffer Rate*, June 2023 for the latest estimate of the Basel gap and supplementary analysis, and Vella, S. (2023). Box 1: A cyclical Systemic Risk Indicator for Malta. In *Financial Stability Report 2022*, pp. 19-22, for the cSRI. The latter is only available from 2006 due to data limitations. The Central Bank of Malta started reporting the Basel gap as a measure of the financial cycle in 2016.

with the household component of the credit gap, and therefore leads the firm credit gap, following the discussion above.[17] Towards the end of the sample the cSRI is affected by the incidence of high inflation, which dampens the dynamics of real bank credit and real total debt growth in that framework, leading to a negative value in 2023Q2. On the other hand, the credit gap based on the multivariate filter is more robust to this, as the model decomposes the level of real credit, rather than its yearly growth rate in deviation from its long run mean. However, the cSRI also conveys the potential for the accumulation of risks when the effect of inflation is controlled for, consistent with the credit gap.

Chart 4
THE CREDIT GAP AND THE cSRI
(% of trend; standard deviations)



Sources: Author's estimates and Vella (2023).

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 presented in this article goes some way towards addressing these challenges in Malta. By filtering credit developments through a semi-structural macroeconomic model, it yields economically meaningful measures of trends, against which the data is assessed. 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 place emphasis on the monitoring of tail risk events.

Over the past few years, the credit gap turned positive through the lens of the semi-structural multivariate filter, as credit growth rose above fundamental growth. The cSRI also points towards similar dynamics in recent years, collectively hinting at rising cyclical risks. Moreover, the credit gap is being driven primarily by the household sector. These findings, together with the low contribution of the corporate sector in the credit gap and the concentration of strong credit growth in the construction and real estate sectors, affirm the appropriateness of the sSyRB on domestic mortgages secured by RRE, which was announced and introduced earlier this year.[18]

[17] The contemporaneous correlation coefficient between the cSRI and the household credit gap is 0.78 over the period 2006Q1 to 2023Q2.
[18] See the full communication of this macroprudential policy decision.