Measuring Credit Gap

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Abstract

This paper proposes a new method to measure credit gap-deviation of credit-to-GDP ratio from its long-run trend. We utilize the idea proposed in Nelson (2008) that the deviation of a non-stationary variable from its long-run trend should predict future changes in the variable. Since different trend-cycle decomposition methods of credit-to-GDP ratio provide us different credit gap measures, we handle the model uncertainty by assigning weights on these different credit gap measures based on its relative out-of-sample predictive power based on Bates and Granger (1969) forecast combination method. We apply this approach to estimate the credit gap for the U.K. and the U.S. using credit-to-GDP ratio data from 1960-2020. Our proposed credit gap measure dominates the alternate credit gaps including the one provided by the Bank of International Settlements (BIS) in terms of its relative out-of-sample predictive power. Our proposed gap also has superior features in terms of early detection of turning points and relative insensitivity to the endpoint problem.

JEL Codes: C52, E44, G01.

Keywords: Credit Gap, Trend Cycle Decomposition, Forecast Combination.

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1 Introduction

There is a consensus in macroeconomics and finance literature about the role of credit in overall macroeconomic activity. Not surprisingly, policymakers and practitioners pay a significant amount of attention to examine if credit growth in the economy is excessive. The problem, however, is that there is no unanimity on how to measure excessive credit. Among different measures of excessive credit, the credit-to-GDP gap measure published by the Bank of International Settlements (BIS) and proposed by Borio and Lowe (2002) has received widespread attention. This measure is estimated by the deviations of the credit-to-GDP ratio from a one-sided Hodrick-Prescott (HP) filter with a large smoothing parameter (400,000 for quarterly data). In subsequent work, Borio and Drehmann (2009), Drehmann et al. (2010), and Drehmann, Borio, and Tsatsaronis (2012) show that the credit-to-GDP gap was the best single Early Warning Indicator across different measures that they examined. Based on this work at the Bank of International Settlements (BIS), the Basel Committee for Banking Supervision (BCBS) has singled out the credit-to-GDP gap as a useful guide for setting countercyclical capital buffers (BCBS 2010b).

The credit gap[1] measure proposed by the BIS is a measure of the cycle based on the HP trend-cycle decomposition of credit-to-GDP ratio, wherein the trend is the best estimate of where the variable will be in the long-run and the cycle is temporary fluctuations around the trend. Since there is no unique method of decomposing a series into a trend and a cycle, it is worth asking if the HP cycle measure used by the BIS is an appropriate measure of the credit gap. In fact, in a recent work Drehmann and Yetman (2021) make a similar argument and attempt to use the idea from Hamilton filter to use linear projections to get an estimate of the credit gap. They find that credit gaps based on linear projections in real time perform poorly when based on country-by-country estimation, and are subject to their own endpoint problems. But when they estimate as a panel, and impose the same coefficients on all economies, linear projections perform marginally better than the baseline

[1] We use the credit gap and credit-to-GDP gap interchangeably throughout this paper.

credit-to-GDP gap, with somewhat larger improvements. This reinforces the argument that there is no unique method of decomposing a non-stationary series into a trend and a cycle, and that we need to take into account model uncertainty in estimating the credit gap.

We propose to use the idea in Nelson (2008), where he argues that if measured cycle component is temporary then it predicts future growth rates of the opposite sign. For example, if the credit-to-GDP ratio is below trend, then a recovery in the ratio will require future growth in the credit-to-GDP ratio at an above-average rate. Conversely, if it is above trend, we can reasonably expect tepid growth in the coming time period. According to Nelson (2008), predictability is the essence of 'transitory' variation, and is expected to be reversed in future periods. Predictability of the cycle provides us with a metric for measuring the effectiveness of alternative decompositions. This idea has also been emphasized by Cogley (2002), Hodrick and Zhang (2003), Orphanides and van Norden (2005), Rotemberg and Woodford (1996) and Wakerly et al. (2006). The idea of predictability implies that a credit gap measure that encompasses all the information from other measures about future movements of the credit-to-GDP ratio is the appropriate credit gap measure. However, in practice, we do not have a measure of the credit gap that possesses this property. This is further complicated by instability in the predictive ability of different credit gap measures that are ubiquitous in the macro forecasting literature.

We combine the idea of predictability with model uncertainty in trend-cycle decomposition by combining credit gap measures obtained from different trend-cycle decomposition methods using weights obtained from the out-of-sample forecasting exercise[2]. The weights are based on the Bates and Granger (1969) algorithm, where we perform a horse race among the most popular trend-cycle decomposition methods in an out-of-sample forecasting exercise[3]. The relative weight on cycles from different trend-cycle decomposition methods is

[2] We use linear trend, quadratic trend, the HP filter, the Ravn and Uhlig (2002) modification of the HP filter, Borio and Lowe (2002) modification of the HP filter, Clark's unobserved component model (1987, Beveridge-Nelson (1981) Decomposition, Hamilton (2018) filter.

[3] Our forecasts are based on 'quasi-real-time' data that uses revised data, but only the observations up to the historical date. When a decomposition requires estimation of parameters, they are re-estimated at each date before computing the cycle estimate.

based on its forecast error variance in predicting out-of-sample credit-to-GDP ratio changes. In addition to taking into account model uncertainty by assigning weights on different models, this approach also handles the instability in the relative forecasting performance of different trend-cycle decomposition methods by assigning time-varying weights on different methods. These weights are time-varying since our method recalculates the weights based on the predictive ability of the model for each iteration in our recursive forecasting exercise.

We apply this approach to the credit-to-GDP ratios of the U.K. and the U.S. and estimate a credit gap measure for the 1994:Q1-2020:Q2 sample period. Our results show that the weighted credit gap measure based on our approach dominates credit gaps from other trend-cycle decomposition methods in out-of-sample forecasting of changes in the credit-to-GDP ratio. Our combined gap measure leads to an improvement of 13 percent for the U.S. and 9 percent for the U.K. for 1-4 quarter ahead forecast horizon over a benchmark AR(1) model. In contrast, the forecasting performance of the BIS gap is worse than the benchmark AR(1) model for both the U.S. and the U.K. In addition, the relative forecasting performance of different methods vary across two countries confirming model uncertainty in the estimation of credit gaps for different methods. Our estimated combined credit gap measure for the U.S. and the U.K. exhibits smooth behavior with a smaller amplitude than the BIS gap. In addition, we observe a clear pattern in early detection of trough date by combined gap in both the countries in comparison to the BIS gap. Finally, the combined gap measure proposed in this paper does not suffer from the endpoint problem usually associated with HP filters.

The remainder of the paper is organized as follows: Section 2 provides brief literature review; Section 3 discusses the data; Section 4 presents our empirical methodology; Section 3 provides a description of the data used in our empirical analysis; Section 5 presents the empirical results; and Section 6 concludes.

2 Related Literature

The importance of the credit gap measured as proposed by Borio and Lowe (2002) can be gauged from the fact that Basel III suggests that policymakers use it as part of their countercyclical capital buffer frameworks. The baseline credit gap of Borio and Lowe (2002) is calculated as deviations of the credit-to-GDP ratio from a one-sided Hodrick-Prescott (HP) filter with large smoothing parameter-400,000 for quarterly data. The smoothing parameter is much larger than the one used for quarterly data in the business cycle literature. This choice of smoothing parameter is rationalized on the ground that credit cycles are on average about four times longer than standard business cycles and crises tend to occur once every 20–25 years (Drehmann et al.2010). Drehmann and Yetman (2021) use the critique of the HP filter outlined in Hamilton (2008) and examine different measures of the credit gap based on different horizons in local projection models. They find that credit gaps based on linear projections in real time perform poorly when based on country-by-country estimation, and are subject to their own endpoint problems. But when they estimate as a panel, and impose the same coefficients on all economies, linear projections perform marginally better than the baseline credit-to-GDP gap, with somewhat larger improvements concentrated in the post-2000 period and for emerging market economies. Several other papers have criticized the HP filter-based credit gap measure. These criticisms are based on the ground that HP filter-based cycle measures generate spurious dynamics and suffer from endpoint problems.

Several papers have tried to resolve this problem. Aikman, Haldane, and Nelson (2015) have used band-pass filters to derive a measure of the credit gap. Galati et al. (2016) estimate a financial cycle using a multivariate unobserved-components model on the credit-to-GDP ratio, total credit, and house prices for six economies, and find that the resulting medium-term cycles vary in terms of length and amplitude across countries and over time. Schuler, Hiebert, and Peltonen (2015) derive a financial cycle based on the common frequencies of credit and asset prices and find that this measure outperforms the credit-to-GDP gap in predicting systemic banking crises at horizons of one-to-three years. Aldasoro, Borio, and

Drehmann (2018) show that combining various indicators of excessive debt with property prices can help to improve financial crisis prediction.

As is widely known, the HP filter is one measure of trend-cycle decomposition. Trend-cycle decomposition has a very rich history in business cycle literature. Yet there is no consensus on what constitutes appropriate decomposition methods. In this paper, we take an agnostic approach and utilize the idea that the cyclical component in the decomposition should have predictive power for future growth of the variable. This idea has been explored in Nelson (2008) to compare the forecasting performance of different trend-cycle decomposition methods for real GDP. We take the predictive ability argument for the cycle one step further and apply it in the context of the estimation of the credit gap. It is widely accepted that model uncertainty reigns supreme in applying a particular trend-cycle decomposition method. To take into account this model uncertainty, we weighted the cycles obtained from different decomposition methods using Bates and Granger forecast combination method.

3 The Data

Our sample periods include quarterly data from 1960:Q1-2020:Q2. Our variable of interest is the credit-to-GDP ratio for the U.S. and the U.K. The data has been sourced from the Bank of International Settlements (BIS). The measure of credit is total credit to the private non-financial sector, as published in the BIS database, capturing total borrowing from all domestic and foreign sources. We do not include data for the recent pandemic period in our analysis. The credit-to-GDP ratios for these two countries are plotted in Figure 1. As can be seen from the figure, these two series are clearly non-stationary. Unit root tests confirm this, with the null of unit root not being rejected at all conventional levels. This is robust to the use of different unit root tests.

4 Empirical Methodology

4.1 Trend-Cycle Decomposition

Our combined measure of the credit gap is based on different trend-cycle decomposition methods for the credit-to-GDP ratio. In the literature, several methods have been proposed to decompose a non-stationary series into a trend and a cycle. Since there is no consensus on the true model of trend-cycle decomposition, we take an agnostic view in this paper. For our purposes, we use seven different measures of trend inflation. All these trend-cycle decomposition methods are based on the premise that a non-stationary series is the sum of a trend and a stationary cyclical component:

$$y_t = \tau_t + c_t \tag{1}$$

where y_t is an I(1) process, and for our purposes, credit-to-GDP ratio. τ_t is trend component and c_t is cyclical component, and is stationary. Trend is usually modeled as random walk and cycle is modeled as following some ARMA(p,q) process. IIn this paper, we use 8 different decomposition methods: linear trend, quadratic trend, the HP filter, the Ravn and Uhlig (2002) modification of the HP filter, Borio and Lowe (2002) modification of the HP filter, Clark's unobserved component model (1987, Beveridge-Nelson (1981) Decomposition, Hamilton (2018) filter. We do not use frequency-based filters because our approach uses the forecasting property of the cycle. The observations at the end of the sample are either not available or highly volatile for frequency-based filters. The linear trend model is based on a deterministic time trend and assumes all variation in headline inflation is transitory, and hence due to cyclical components. The HP filter is an atheoretical smoothing method to obtain trend and cycle components of non-stationary series and is very popular in macroeconomics and finance literature. We follow the original prescription of Hodrick and Prescott (1997) and use smoothing parameter λ=1600 for our quarterly credit-to-GDP ratio data. Ravn and Uhlig (2002) have suggested modifying the smoothing parameter to account for the frequency of the data. Following their suggestion we use smoothing parameter λ=3000 for the other model. We call this model RU in our exercise. Higher λ yields a much smoother trend. Our unobserved component model is based on the original Clark's (1989) model. In particular, trend follows a random walk and cycle has ARMA (p,q) representation. Both trend shocks and cyclical shocks have time-varying volatility.

$$\tau_t = \tau_{t-1} + \eta_t, \eta_t \tilde{} iid(0, \sigma_\eta^2) \tag{2}$$

$$c_t = \Phi(L)c_t + u_t, u_t \tilde{} iid(0, \sigma_u^2) \tag{3}$$

Beveridge-Nelson (1981) methodology decomposes a non-stationary series into a random walk component and a stationary component which is the cycle of the non-stationary series. The BN decomposition of z_t has the following representation:

$$y_t = y_0 + \mu t + \Psi(1) \sum_{k=1}^{t} u_t + \breve{u}_t - \breve{u}_0 \tag{4}$$

where $\Psi(1) \sum_{k=1}^{t} u_t$ is the stochastic trend and $\breve{u}_t - \breve{u}_0$ represents the cycle. BN proposed that the long-run forecast is a measure of trend for time series such as GDP that do not follow a deterministic path in the long run. They showed that if the series is stationary in first differences, then the estimated trend is a random walk with drift that accounts for growth, and the cycle is stationary. In contrast to HP and UC decomposition, the BN decomposition attributes most variation in non-stationary series to trend shocks while the cycles are short and brief. In addition to these decomposition methods, we also use Hamilton (2018) approach to calculate credit gap. Hamilton (2018) argues that HP filter produces spurious dynamics that are not based on the underlying data-generating process and the dynamics at the ends of the sample differ from those in the middle. Hamilton (2018) proposes calculating cycle from the residual of the following linear projection model

$$y_{t+h} = \alpha + \beta_1 y_{t--1} + \beta_2 y_{t--2} + ... + \beta_p y_{t--p} + v_{t+h} \tag{5}$$

The estimated residual $\widehat{v}_{t+h}$ is the cyclical component from this approach. Hamilton suggests using h=8 for quarterly data and that is what we follow in our estimation.

4.2 Forecasting Model

Once the credit gap measures are obtained from different trend-cycle decomposition methods, we regress growth rate of credit-to-GDP ratio on its own lags and lags of credit gap. In particular, we estimate the following model:

$$\Delta y_t = \alpha + \beta(L)\Delta y_{t-1} + \gamma(L)GAP_{t-1} + v_t \tag{6}$$

The lags are chosen based on the Bayesian Information Criterion (BIC). We generate the forecasts from the above model for credit gaps generated from different trend-cycle decomposition approaches. Our benchmark model is an AR(1) model. We compare the forecasts generated from the above model with this benchmark model to examine if the inclusion of lagged credit gap leads to an improvement in forecasting performance of growth rate of credit-to-GDP ratio.

4.3 Forecast Combination

Once we have different measures of cycle, we use Bates and Granger (1969) method of forecast combination to assign weights to different cycles. The underlying idea is that the cyclical component should be able to predict changes in credit-to-GDP ratio. Bates-Granger weights are based on the following formula:

$$w_m = \frac{\widehat{\overline{\sigma}}_m^2}{\widehat{\overline{\sigma}}_1^2 + \widehat{\overline{\sigma}}_2^2 + ...\widehat{\overline{\sigma}}_M^2} \tag{7}$$

where $\widehat{\overline{\sigma}}_m^2$ is inverted out-of-sample forecast error variance of forecast M based on the cyclical component M. M is the number of forecasts. Weights are normalized by sum of inverted forecast error variances. Here the weight is assigned based on the predictive ability of different cycles.

5 Empirical Results

Our analysis is performed in three steps: In the first step, we calculate the credit gap from 8 different trend cycle decomposition methods. These methods are: conventional HP filter (1997), Ravn-Uhlig's (2002) modification of the HP filter, HP filter with a high smoothing parameter (BIS gap), Beveridge-Nelson decomposition, Hamilton filter, Unobserved component model, linear trend, and quadratic trend. We perform these estimations recursively to preserve the 1-sided nature of the credit gap. Our first estimation sample runs from 1960:Q1-1988:Q4 and saves the last estimate of the cycle. We keep adding one more observation to the estimation sample and keep saving the last observation of the cycle for different methods. This approach provides us with a 1-sided estimate of the credit gap from different methods. In the second step, we use these 1-sided credit gap measures to forecast changes in the credit-to-GDP ratio. The estimation sample for the first forecasts is 1989:Q2-1994:Q1. We then move ahead one quarter, re-estimate the forecasting model and forecast 1995:Q2-1996:Q1, etc. Our final set of forecasts, for 2019:Q3 2020:Q2, would have been prepared in 2019:Q2. We consider different quarterly horizon forecasts until Q=4. In addition to these quarterly forecasts, we also examine the average over the next four quarters. These averages are also used in the analysis to get around the noise associated with quarterly projections.

Tables 1 and 2 show the out-of-sample forecasting results for the above exercise for the U.K. and the U.S. The tables show the ratio of root mean squared errors in comparison to a benchmark AR(1) model. The ratio of less than unity implies that the model in question has a lower RMSE than the benchmark AR (1) model. The results are reported for eight different methods of trend-cycle decomposition and two forecast combination methods. Our preferred forecast combination method is Bates and Granger, though we also report the simple average of different forecasts. The results clearly suggest a significant improvement in forecasting performance using our combination approach. For the U.S., there is an improvement of around 13 percent in the RMSE over the benchmark AR(1) model if we combine the forecasts based on the BG approach. Interestingly, for the U.S., the inclusion of the BIS gap in the forecasting equation (6) leads to a deterioration in forecasting performance. The conventional HP filter does a better job than Ravn-Uhlig and the BIS measure. Deterministic trend models also do not perform well. The credit gap measures obtained from the BN and the UC models perform better than the benchmark AR(1) model implying that inclusion of the lagged credit gap measure improves forecasting performance. For the U.K., the BG method yields an improvement of 9 percent in RMSE over the benchmark AR(1) model over h=1-4 forecasting horizon. Even for the U.K., the BIS gap measure does not lead to an improvement in forecasting performance. The BN approach that improved the forecasting performance in the case of the U.S. performs poorly in the U.K. Overall, results for the forecasting exercise validate our argument that focusing on a single measure of trend-cycle decomposition to derive a measure of credit gap is fraught with severe limitations. The forecast combination that assigns weights based on the predictive performance not only takes into account this model uncertainty, but in doing so improves the metric-forecasting performance- that should be the evaluation criteria for different trend-cycle decomposition methods.

Figures 2 and 3 plot the credit gaps obtained from our forecast combination approach along with the BIS credit gaps for the U.K. and the U.S. The sample period for the credit gap is 1994:02-2020:02. There are several interesting features that emerge from these graphs. First, we find that both the gap measures do move together. This is not surprising since the combined gap measure is a weighted measure of different cycle measures. Both the measures suggest that the credit-to-GDP ratio was above its long-run trend before the crisis for the U.K. and the U.S. These two measures became negative in the aftermath of the financial crisis and stayed negative for a significant time period. Although these credit gap measures tend to move together broadly, there are also significant differences within different sub-samples. For the U.S., the combined credit gap became positive three years earlier than the BIS gap implying that the credit-to-GDP ratio was above its long-run trend starting in 1995:Q2. This was also the time period when the boom in the housing market started in the U.S. A similar pattern is observed in the U.K., where the combined gap became positive a year (in 1998:Q3) earlier than the BIS gap. Interestingly, there is no significant difference in the timeline when these gap measures turn negative.

Secondly, we find that the combined credit gap measure is significantly less volatile than BIS gap. The standard deviation of the combined gap is 6.84, whereas it is 11.57 for the BIS gap for the U.K. The corresponding numbers are 5.16 and 8.66 for the U.S. This becomes particularly evident during the post-financial crisis period where the trough of the cycle is significantly lower for the BIS gap than the combined gap for both the countries. The lower volatility of the combined gap is expected since it is derived from a weighted combination of different gap measures. This difference is even more stark for the U.K. than the U.S. Not only is there a significant differential between these two different credit gap measures after the financial crisis, these differences have persisted for a long period of time. Thirdly, we observe a clear pattern in early detection of trough date by combined gap in both the countries. For the U.S., the trough of the cycle is 2012:Q3 according to the combined gap measure, whereas it occurred in 2013:Q1 according to the BIS measure. For the U.K., the combined gap suggests that the gap reached its bottom in 2015:Q1, whereas the corresponding date was 2015:Q2 for the BIS gap. For the peak, we do not find significant differences in the detection of turning points.

The comparison of credit gap measures across these two countries provides interesting insights. The peak in the credit-to-GDP ratio was reached in the U.K. much earlier than the beginning of the financial crisis. The peak for the U.K. as measured by these credit gap measures took place at the end of 2002 and the gap did not display any trend until the end of 2008. In the U.S., however, the peak occurred just before the financial crisis. Although both credit gap measures were positive before the crisis, the difference between them grew. Both the measures fell at a rapid pace for the U.S. during the crisis. In the U.K., however, the BIS gap measure fell at a much faster rate and the difference between these two measures started growing much earlier. The results from our forecasting exercise suggest that the rapid pace of fall in the credit gap for the BIS measure may have been overestimated. The results also suggest that the gap Finally, one of the criticisms of the HP filter is that it suffers from the endpoint problem. This can be observed in our figures where both BIS gap measures for the U.S. and the U.K. show a sudden shift at the end of the sample and display a ragged edge problem. Our combined gap does not suffer from this problem.

6 Conclusions

This paper proposes an alternate measure of credit gap-deviation of credit-to-GDP ratio from long-run trend. Our credit gap estimation approach is based on the premise that the deviation of a non-stationary time series from its trend should have predictive power for subsequent movements in the changes in the variables as noted by Nelson (2008). In addition, we also take into account the model uncertainty by acknowledging that there is not a unique way to decompose a series into a trend and a cycle. For this purpose, we assign weights to different credit gaps derived from different trend-cycle decomposition methods. These weights are based on the out-of-sample forecast error variance as in Bates and Granger (1969). Our results show that this method of combining credit gaps yield us a credit gap measure that dominates credit gaps from different trend-cycle decomposition methods including the one published by the BIS in terms of superior out-of-sample forecasting of changes in credit-to-GDP ratio. We apply this framework to the data from the U.S. for the recent time period. We also show that our proposed credit gap measure captures the trough in the credit cycle earlier than the BIS measure and also displays lower volatility.

References

[1] Aikman, D., Haldane, A. G., & Nelson, B. D. (2015). Curbing the credit cycle. The Economic Journal, 125(585), 1072-1109.

[2] Aldasoro, I., Borio, C. E., & Drehmann, M. (2018). Early warning indicators of banking crises: expanding the family. BIS Quarterly Review, March.

[3] Basel Committee on Banking Supervision (BCBS) (2010a). An Assessment of the Long-term Economic Impact of Stronger Capital and Liquidity Requirements. Bank for International Settlements (August).

[4] Basel Committee on Banking Supervision (BCBS) (2010b). Guidance for National Authorities Operating the Countercyclical Capital Buffer. Bank for International Settlements (December).

[5] Bates, J. M., & Granger, C. W. (1969). The combination of forecasts. Journal of the Operational Research Society, 20(4), 451-468.

[6] Beveridge, S., & Nelson, C. R. (1981). A new approach to decomposition of economic time series into permanent and transitory components with particular attention to measurement of the 'business cycle'. Journal of Monetary economics, 7(2), 151-174.

[7] Borio, C. E., & Lowe, P. W. (2002). Asset prices, financial and monetary stability: exploring the nexus.BIS Working Paper No. 114.

[8] Borio, C. E., & Drehmann, M. (2009). Assessing the risk of banking crises–revisited. BIS Quarterly Review, March.

[9] Clark, P. K. (1987). The cyclical component of US economic activity. The Quarterly Journal of Economics, 102(4), 797-814.

[10] Cogley, T., & Nason, J. M. (1995). Effects of the Hodrick-Prescott filter on trend and difference stationary time series Implications for business cycle research. Journal of Economic Dynamics and control, 19(1-2), 253-278.

[11] Drehmann, M., Borio, C. E., Gambacorta, L., Jimenez, G., & Trucharte, C. (2010). Countercyclical capital buffers: exploring options. BIS Working Paper No. 317.

[12] Drehmann, M., Borio, C., & Tsatsaronis, K. (2011). Anchoring Countercyclical Capital Buffers: The Role of Credit Aggregates. International Journal of Central Banking 7 (4, December): 189–240.

[13] Drehmann, M., & Tsatsaronis, K. (2014). The credit-to-GDP gap and countercyclical capital buffers: questions and answers. BIS Quarterly Review (March): 55–73.

[14] Drehmann, M., and J. Yetman (2018). Why You Should Use the Hodrick-Prescott Filter — At Least to Generate Credit Gaps. BIS Working Paper No. 744.

[15] Edge, R., and R. Meisenzahl (2011). The Unreliability of Credit-to-GDP Ratio Gaps in Real-Time: Implications for Countercyclical Capital Buffers. International Journal of Central Banking 7 (4,December): 261–98.

[16] Galati, G., Hindrayanto, I., Koopman, S. J., & 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.

[17] Hamilton, J. (2018). Why You Should Never Use the Hodrick-Prescott Filter. Review of Economics and Statistics 100 (5):831–43.

[18] Hodrick, R., and E. Prescott (1997). Postwar U.S. Business Cycles: An Empirical Investigation. Journal of Money, Credit and Banking 29 (1): 1–16.

[19] Hodrick, Robert J., Zhang, Xiaoyan (2003). Forecasting real GDP growth with Hodrick–Prescott filtered components: An out-of-sample analysis. Discussion paper

[20] Jorda, O. (2011). Discussion of ‘Anchoring Countercyclical Capital Buffers: The Role of Credit Aggregates. International Journal of Central Banking 7 (4, December): 241–59.

[21] Jorda, O., B. Richter, M. Schularick, and A. Taylor (2017). Bank Capital Redux: Solvency, Liquidity, and Crisis. NBER Working Paper No. 23287.

[22] Nelson, C. R. (2008). The Beveridge–Nelson decomposition in retrospect and prospect. Journal of Econometrics, 146(2), 202-206.

[23] Orphanides, A., & Norden, S. V. (2002). The unreliability of output-gap estimates in real time. Review of economics and statistics, 84(4), 569-583.

[24] Ravn, M., and H. Uhlig (2002). On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations. Review of Economics and Statistics 84 (2): 371–76

[25] Rotemberg, J. J., & Woodford, M. (1996). Real-business-cycle models and the forecastable movements in output, hours, and consumption. The American Economic Review, 71-89.

[26] Schüler, Y. S., Hiebert, P., & Peltonen, T. A. (2015). Characterising the financial cycle: a multivariate and time-varying approach.

[27] Wakerly, E. C., Scott, B. G., & Nason, J. M. (2006). Common trends and common cycles in Canada: who knew so much has been going on?. Canadian Journal of Economics/Revue canadienne d’économique, 39(1), 320-347.

Figure 1: Credit-to-GDP Ratios

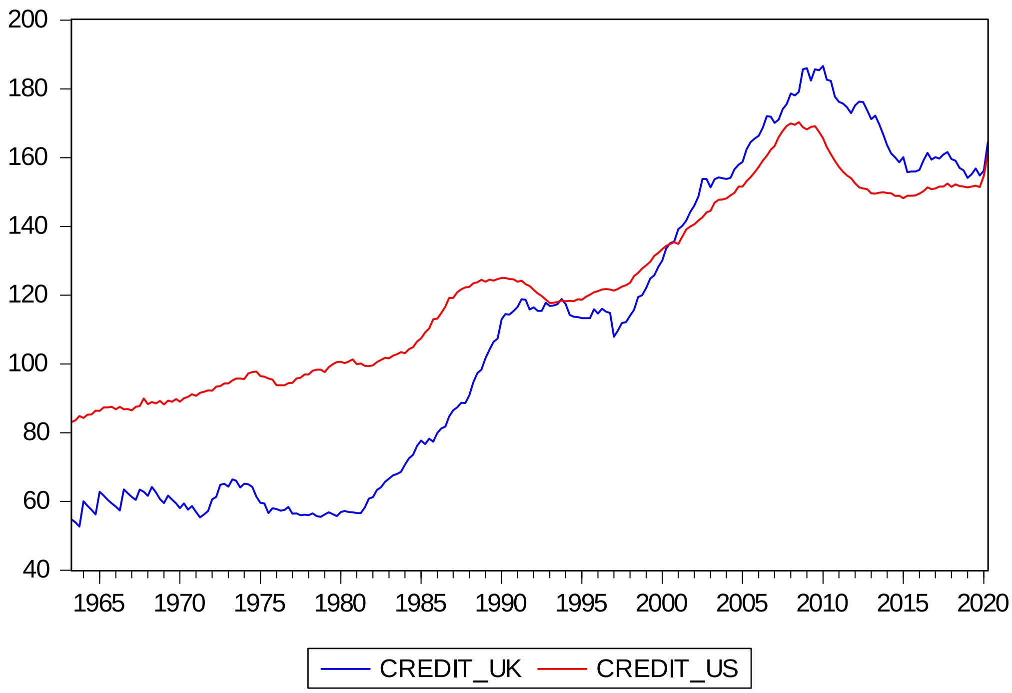

Figure 2: Credit Gap Comparison (U.K.)

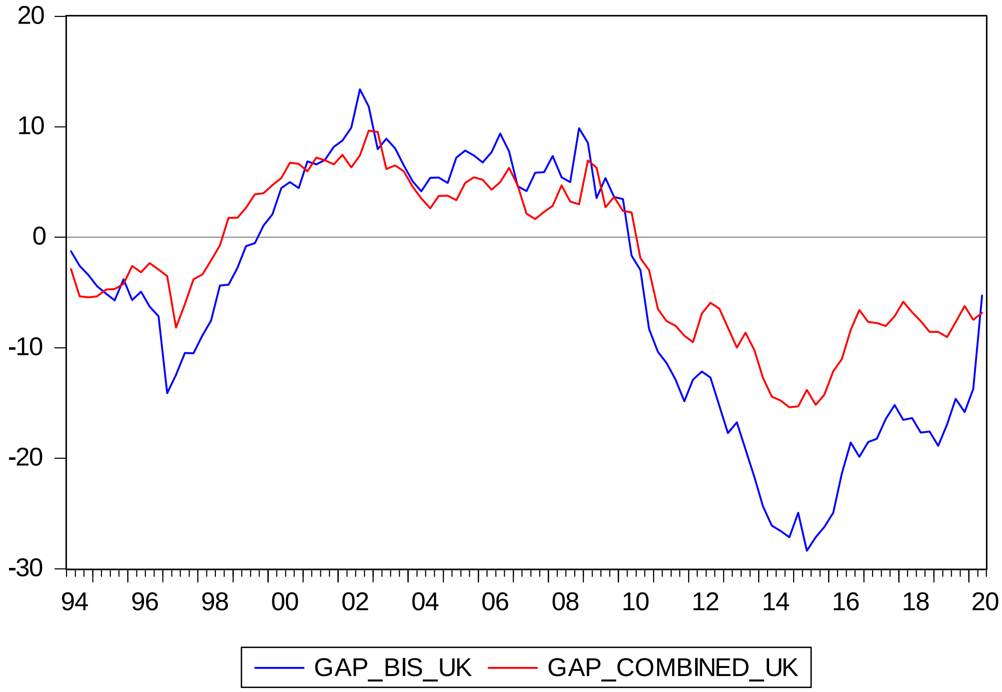

Figure 3: Credit Gap Comparison (U.S.)

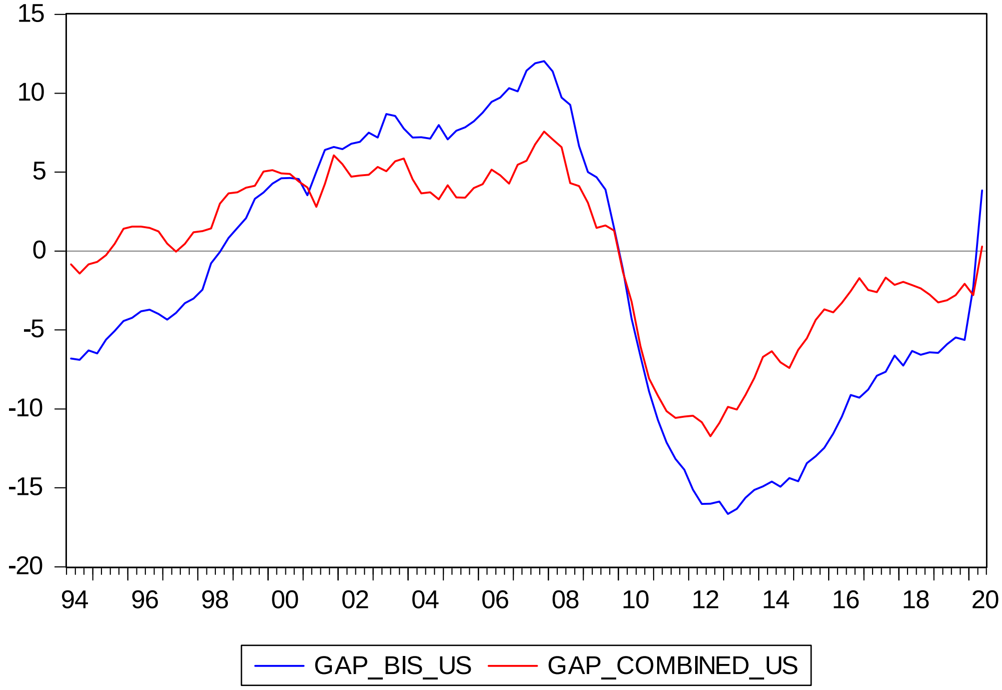

Table 1. Forecasting Performance of Credit Gap Models (U.K.)

Horizon	HP	RU	BIS	Hamilton	Linear	Quadratic	BN	UC	Average	Bates-Granger
1	1.001	0.990	1.001	0.992	1.010	0.979	1.028	1.009	0.977	**0.979**
2	0.979	0.970	1.007	0.969	1.016	0.962	1.028	0.999	0.962	**0.957**
3	0.979	0.971	1.018	0.969	1.055	0.966	1.009	0.989	0.959	**0.955**
4	0.990	0.987	1.028	1.005	1.055	0.981	1.019	0.981	0.972	**0.967**
1 - 4	0.972	0.952	1.034	0.960	1.081	0.929	1.054	0.985	0.918	**0.910**

Notes:

The table shows the ratio of RMSEs of different models in comparison to the benchmark AR(1) model. The first set of forecasts is for 1994:Q1-1994:Q4; the final set is for 2019:Q3-2020:Q2. Q=1-4 denotes averages over next 4-quarters. HP is Hodrick-Prescott, RU is Ravn-Uhlig, BIS is based on Borio and Lowe (2002), BN is Beveridge-Nelson, UC is Unobserved Component Model. The smallest ratio in each row is bolded.

Table 2. Forecasting Performance of Credit Gap Models (U.S.)

Horizon	HP	RU	BIS	Hamilton	Linear	Quadratic	BN	UC	Average	Bates-Granger
1	0.993	0.987	1.012	0.994	1.028	1.005	1.010	0.985	0.962	**0.959**
2	0.974	0.963	1.016	0.980	1.058	1.014	0.975	0.961	0.924	**0.917**
3	0.966	0.953	1.023	1.011	1.055	1.036	0.965	0.937	0.906	**0.896**
4	0.982	0.966	1.022	1.029	1.055	1.045	1.033	0.910	0.922	**0.910**
1 - 4	0.964	0.945	1.030	1.005	1.081	1.041	0.978	0.913	0.882	**0.872**

Notes:

The table shows the ratio of RMSEs of different models in comparison to the benchmark AR(1) model. The first set of forecasts is for 1994:Q1-1994:Q4; the final set is for 2019:Q3-2020:Q2. Q=1-4 denotes averages over next 4-quarters. HP is Hodrick-Prescott, RU is Ravn-Uhlig, BIS is based on Borio and Lowe (2002), BN is Beveridge-Nelson, UC is Unobserved Component Model. The smallest ratio in each row is bolded.