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Weighing up the Credit-to-GDP gap: A cautionary note*

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Abstract

It has been argued that credit-to-GDP gaps (credit gap) are useful early warning indicators for banking crises. In addition, the Basel Committee on Banking Supervision has also advocated using these gaps - estimated using a one-sided Hodrick-Prescott filter with a smoothing parameter of 400,000 - to inform policy on the appropriate counter-cyclical capital buffer. We use the weighted average representation of the same filter and show that it attaches high weights to observations from the past, including the distant past: up to 40 lags (10 years) of past data are used in the calculation of the one-sided trend/permanent component of the credit-to-GDP ratio. We show how past data that belongs to the 'old-regime' prior to the crises continue to influence the estimates of the trend for years to come. By using narrative evidence from a number of countries that experienced deep financial crises, we show that this leads to some undesirable influence on the trend estimates that is at odds with the post-crisis environment.

JEL Codes: J31, J64

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1. Introduction

In the wake of the Global Financial Crisis, the Basel Committee on Banking Supervision (BCBS) argued for counter-cyclical capital buffers, and published operational guidelines (BCBS (2010)) for regulators. The cornerstone of the BCBS proposal is the use of cyclical movements in the credit-to-GDP ratio gap to trigger increases in the capital required to be held by banks. The Basel Committee recommendations were empirically supported by Drehmann (2014) and Drehmann and Tsatsaronis (2014), who argued that credit-to-GDP ratio gaps (credit gaps herein) are useful, if imperfect, leading indicators of banking crises.

Drehmann (2014) and Drehmann and Tsatsaronis (2014), following Borio and Lowe (2002) and Borio and Lowe (2004), use a one-sided Hodrick-Prescott (HP) filter applied to the credit-to-GDP ratio with a smoothing parameter of 400,000. Drehmann et al. (2010) argue that the credit-to-GDP ratio provides a normalisation of credit in order to take into account the fact that credit demand and supply grow in line with the size of the economy.[1] Borio and Lowe (2004), who first used the smoothing parameter of 400,000, argued that "*it meant that the trends are smoothed considerably more than normal, better capturing low-frequency, cumulative deviations, and implicitly putting more weight on the mean-reversion tendency of the processes*".

Drehmann et al. (2010) argue that they focus on the gap in the credit-to-GDP ratio because they want '*to take account of possible changes in the long-run level of the [credit-to-GDP] ratio, for example due to financial deepening*.' At the same time, Drehmann et al. (2010) and Drehmann (2014) motivate the choice of the smoothing parameter to match the duration of financial cycles. After comparing the credit-to-GDP gap estimates from four different values of λ they conclude that the gaps based on $\lambda = 400,000$ perform best. They further argue that this is not surprising, as credit cycles should be three or four times longer than business cycles.[2]

In this note, we use the weighted average representation of the trend/permanent component of the HP filter used in Drehmann et al. (2010), Drehmann (2014) and show some undesirable effects of the filter used in the trend estimates. Any filter, including a one-sided

[1] A similar normalisation could be achieved by calculating per-capita real credit.

[2] Four different values for λ are $1600 \simeq 1^4 * 1600$, $25000 \simeq 2^4 * 1600$, $125000 \simeq 3^4 * 1600$ and $400000 \simeq 4^4 * 1600$, which correspond to the financial cycles having the same, double, triple and quadruple length of business cycles (BCBS (2010)).

HP filter, can be written as the weighted average of the past (and future) data. One can therefore evaluate how the estimates of the trend or the permanent component (and by definition the cyclical component) are related to the actual data. We identify two issues.

First, a higher smoothing parameter means that past information receives more weight in determining the current estimate of the trend. For example, the latest available observation receives a 6.1% weight, while observations from 10, 20 and 30 quarters ago receive weights of 4.4%, 2.8% and 1.5% respectively. In other words, the distant past continues to influence the estimates of trend. These weights are different than the two-sided weights with the same smoothing parameter.[3]

Second, the weighing of the past dies out significantly more slowly relative to lower smoothing parameters. It takes up to 40 quarters for a particular observation to drop out of the trend estimates. This slow decline of past information in weighted averaging, combined with flatter (more equal) weights attached to them, mean that the trend estimates are very smooth and the resulting gaps are almost non-stationary.

These two features of the filter cause some undesirable properties for the trend estimates: for example, if the observed credit-to-GDP series is driven by excess credit growth the estimated trend would reflect this fact even though the true trend should not influenced by it. This is particularly problematic where there are clear regime changes. We use examples of financial crises where credit conditions changed dramatically, as our laboratory to examine the filter. More specifically, we use narrative evidence from Argentina and Malaysia that experienced financial crises and show that the effects of 'excessively' high past credit-to-GDP data influence the trend estimates in post-crisis periods. Even though credit conditions changed dramatically following their crises, we find that the effects of old data influence the trend estimates even after 10 years, which in theory should not be the case given crises are clear structural breaks in trends.

The point we are highlighting in this note is not an econometric or a filtering one, but an economic one. We show that the trend estimates based on the HP filter weigh information from the distance past heavily. If there are regime changes, or the past credit-to-GDP ratio data includes some 'credit boom/excesses' those observations should have no say on where

[3]Had the policymakers had the future data, they would have attached lower weights to the past data, in other words.

the trend is at the end of history.[4] We argue that these findings indicate that caution should be taken when using these gaps mechanically. By using the weighted average representation of the one-sided HP filter, we show that structural breaks lead to undesirable properties in the estimation of trends. Drehmann and Tsatsaronis (2014), using simulations, make a similar point and suggest that structural breaks take twenty years to fully disappear.

A number of papers examined credit gaps from a number of angles. Edge and Meisenzahl (2011) compare the one-sided (real-time) estimates to the ex-post, final estimates. At the same time, Buncic and Melecky (2014) argue that the credit gap is not necessarily related to any equilibrium level of credit. In other words, no formal model underpins the choice of the indicator proposed by the BCBS. Theoretically, Drehmann and Tsatsaronis (2014) make the case that the credit gap encapsulates the arguments of Kindleberger (1978) and Minsky (1982), who warned that financial crises are products of debt accumulation fueled by excessive credit growth.

Most research does not make a distinction between credit that is extended to different agents for different reasons: households or firms, or credit that is extended for new investment or for the exchange of existing assets, for example housing. These two types of credit might have different implications for the economy, and different effects on the macroeconomy and asset prices (Bahadir and Gumus (2016) and Mian et al. (2017)).

Credit can also be extended for working capital purposes, or purposes of keeping the customers afloat. For example, during dairy price downturns, New Zealand banks are known to extend credit to farmers to prevent them from going into foreclosures. Changes in domestic currency returns from commodity prices can often times be temporary and timely credit can smooth these short-term fluctuations.

The rest of this note is structured as follows: Section 2 examines the basic properties of the credit-gap estimates from the BIS by means of the tests proposed by Cogley (2002). Section 3 shows the weighted average representation of the HP filter, and discusses the implications of these weights for trend estimates. Section 4 uses a narrative approach to examine the implications of these weights for countries that have experienced financial crises, and section 5 concludes.

[4]Similar findings can be observed in estimating the trend growth rate of output with the HP filter: one large drop in output growth, or natural disasters, can have strong influences on the trend growth rate estimates. We thank Adrian Pagan for pointing this out to us.

2. Testing Trends: Cogley (2002)

We follow Cogley (2002) and test whether the credit-to-GDP ratios converge in the future to the estimated trends. This test was first introduced by Cogley (2002) to examine the properties of the US core inflation estimates, and since then has been applied to core inflation or other unobserved variables[5] Because the estimated trends are designed to strip out transitory factors, the Cogley (2002) method explicitly tests whether the estimated trends represents the permanent component of the series - credit-to-GDP ratios in our case. As Kamber and Wong (2016) stress, while the definition we apply may be narrow, the Cogley (2002) test is very precise in terms of what is being evaluated. The basic idea of the test is that if actual observed series (credit-to-GDP ratio) is above (below) current trend estimate, the actual series should fall (increase) to converge back to trend at some future horizon, h.

Let x_t and x_t^* be observed the credit-to-GDP ratio and the trend credit-to-GDP ratio at time t, respectively. The idea of an observed series x_t converging back to trend, x_t^* at some future horizon can be represented by the following equation:

$$Ex_{t+h} = x_t^* \tag{1}$$

Equation 1 states that at time t, given that the observed credit-to-GDP series is expected to converge to its trend in the future, the expectation of the actual credit-to-GDP ratio h periods ahead is the trend at time t. If we subtract the current level of trend from both sides we get equation (2):

$$Ex_{t+h} - x_t = -(x_t - x_t^*) \tag{2}$$

which can be estimated by OLS in the form of equation (3):

$$x_{t+h} - x_t = \alpha + \beta(x_t - x_t^*) + \epsilon_t \tag{3}$$

Equation 2, which follows from equation 1, simply states that assuming the original definition from equation 1 holds, the differences between the observed series h periods ahead from

[5] Recently, Berger et al. (2019) applied the same test for the “trend” capital flows estimates, KF*.

now, is just the negative of today's gap between the observed series and the estimated trend. In other words, at some horizon h, the effects of temporary factors dissipate, and all we are left with is trend. Equation 3 provides a relationship that can be used to test the definition embodied in Equation 1. Again, assuming that the definition we started with in Equation 1 holds, a measure of the trend consistent with our definition would produce estimates of $\alpha = 0$ and $\beta = 1$ if we estimate Equation 3.

If α is different from zero, it suggests that the measure of trend credit-to-GDP ratio is biased. If β is smaller than -1, then the trend measure of credit-to-GDP ratio is potentially stripping out too little. In other words, some of the transitory factors are not stripped out at a particular horizon h, and the measure of trend is contaminated by the transitory factors. Conversely, if β is greater than -1, the trend measure is potentially stripping out too much. In other words, part of the permanent component of credit-to-GDP ratio is being stripped out.

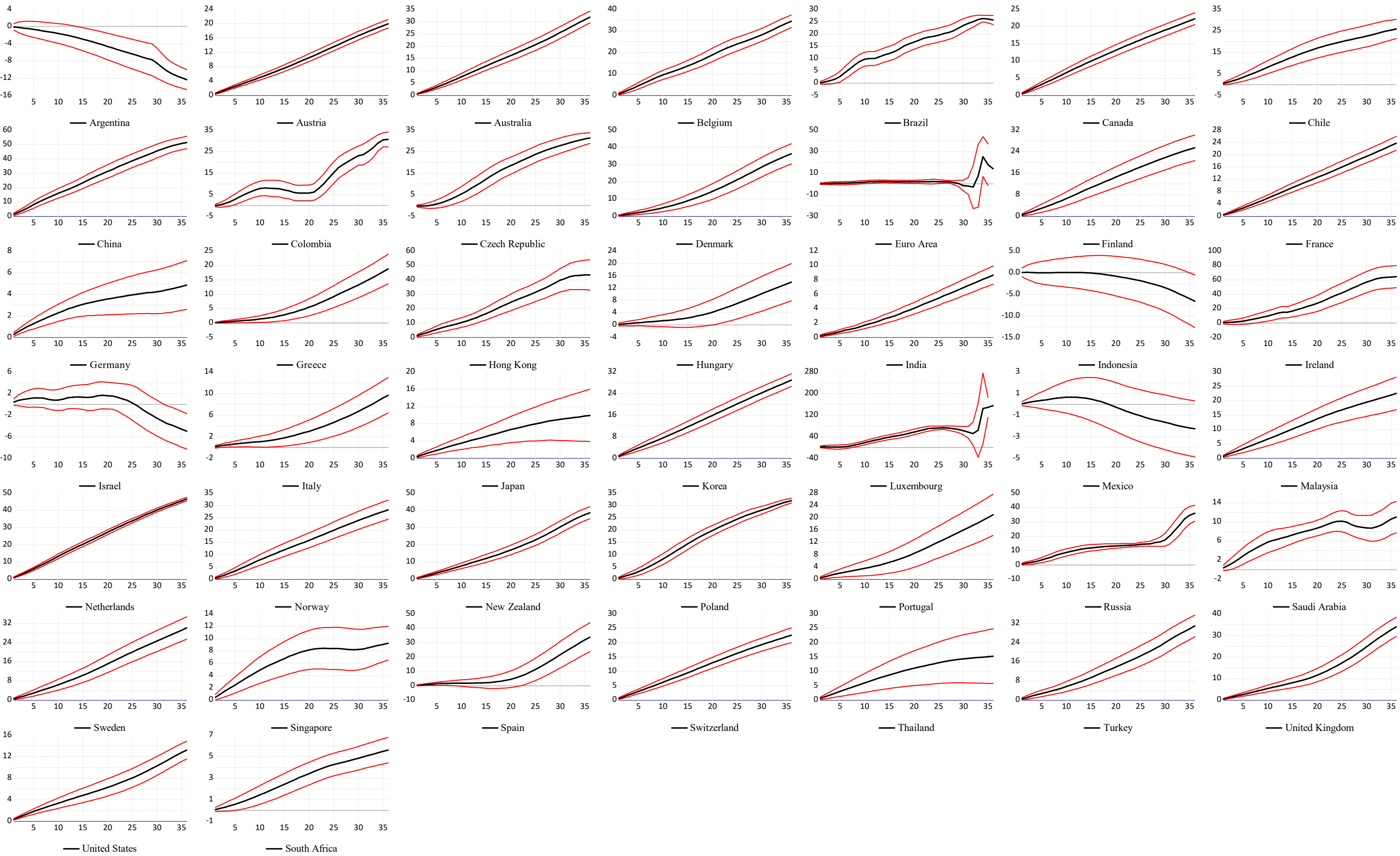
It is important to note that the econometric tests we conduct are not informative about the current level of trend credit-to-GDP ratios. We essentially test whether, on average over the sample, the trend measures estimated from the HP filters deliver the particular joint restrictions on the parameters α and β. Therefore our test should not be seen as a forecasting exercise.

It is not a priori obvious what the appropriate horizon over which observed credit-to-GDP ratio should converge back to trend. We therefore report the estimated values of parameters α and β for horizons up to 36 quarters, a longer horizon than considered in Cogley (2002) and Kamber and Wong (2016), given the longer length in financial cycles.[6]

Figure 1 presents the estimated constant, α and Figure 2 presents the coefficient estimate for β for a sequence of regressions indexed by horizon h. The dotted lines represent 95 percent confidence intervals associated with each point estimate. We can conclude from Figure 1 that there is no evidence that any estimated trend is unbiased across countries with the exception of Mexico and, possibly Finland. For a number of countries, in the horizons we are concerned with, the α coefficient is significantly different from zero. Moreover, in almost every country, the same coefficient is significantly different than zero at every horizon.

[6]Beyond 36 quarters the degrees of freedom becomes an issue in estimation. Moreover, given the smooth nature of the estimated parameters across h we could infer their likely path at horizons beyond 36 quarters.

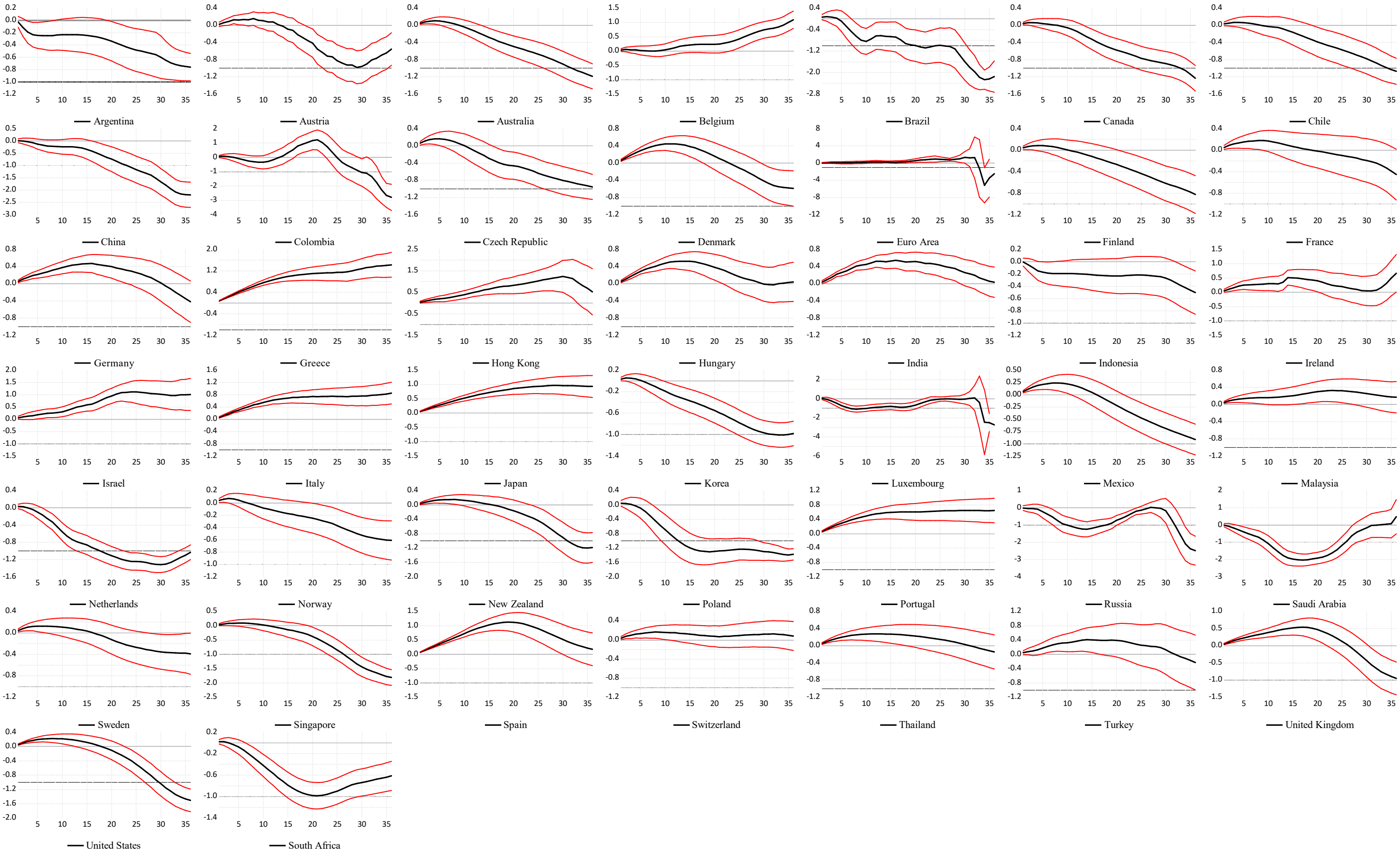
Figure 1
Estimated α and 95% error band



Note: Black lines are the coefficient estimates at each horizon, h, and the red lines are the 95 percent confidence bands.

Figure 2

Estimated β and 95% error band



Note: Black lines are the coefficient estimates at each horizon, h, and the red lines are the 95 percent confidence bands.

We present the coefficient estimates of β in Figure 2. Again, we mainly focus at the longer end of those horizons (i.e. h at 24-36 quarters ahead) given the length of financial cycles. For fourteen countries out of 44 countries by $h = 36$ quarters the estimated coefficient converges to -1. These countries are Argentina, Australia, Canada, Chile, Czech Republic, Denmark, the Euro area, Finland, Korea, Mexico, the Netherlands, New Zealand, Turkey and the United Kingdom. This implies that the filter does satisfy the test proposed by Cogley (2002). It also appears that for some countries the estimated coefficient β would have converged to -1 at some horizon beyond $h = 36$.

For a larger share of countries in the sample the estimated coefficients are significantly different than -1 by horizon $h = 36$, implying that the filter is either stripping too much or too little. In other words, in the case of over-stripping, the filter strips out some of the permanent component or vice versa. Overall, these results suggest that there is no single smoothing parameter, λ, that would fit every country by this metric.

3. The Hodrick-Prescott Filter as a Weighted Average

There are many different ways to characterise the Hodrick-Prescott (HP) filter. Probably the simplest one, and easiest to understand is thinking about the HP filter as a weighted average of the data.[7] The Hodrick-Prescott approach to filtering can be thought of as a weighted average of data, where the weights are chosen to make the trend/permanent component of the series y_t^τ a smooth series, and involves the following minimization problem:

$$\min_{y_t^\tau} \sum_{t=1}^{T} (y_t - y_t^\tau)^2 + \lambda(\Delta y_{t+1}^\tau - \Delta y_t^\tau)^2 \tag{4}$$

[7] Cogley and Nason (1995) showed that the trend component of the HP filter can be approximated by first calculating the fourth-differences of the original data and then taking a long, smooth, weighted average of past and future values of those differences. For a deeper discussion on different characterisations of the HP filter, see Hamilton (2018) and deJong and Sakarya (2016). For some earlier treatments of the same filter, particularly on the smoothing parameter see Ravn and Uhlig (2002) and Harvey and Jaeger (1993). van-Norden and Wildi (2015) analyse the HP filter from a number of perspectives including the sample size and their relevance for the weights.

for a choice of the smoothing parameter, λ. Equation 4 tries to minimise the deviations of the series from its trend (the first term in the equation) and the lack of smoothness in the trend component (the second term). Equation 4 can be re-written using lag operators:

$$\begin{aligned}\min_{y_t^*} &= \sum_{t=1}^{T}(y_t - y_t^{\tau})^2 + \lambda \sum_{t=1}^{T}((L^{-1} - I)y_t^{\tau} - (I - L)y_t^{\tau})^2 \\ &= \sum_{t=1}^{T}(y_t - y_t^{\tau})^2 + \lambda \sum_{t=1}^{T}((L^{-1} - 2I + L)y_t^{\tau})^2 \\ &= \sum_{t=1}^{T}(y_t - y_t^{\tau})^2 + \lambda \sum_{t=1}^{T}(L^{-1} - 2I + L)^2 y_t^{\tau})^2 \\ &= \sum_{t=1}^{T}(y_t - y_t^{\tau})^2 + \lambda \sum_{t=1}^{T}(L^2 - 4L^{-1} + 6I - 4L + L^2)(y_t^{\tau})^2\end{aligned} \tag{5}$$

where the last term represents a fifth-order moving average in the squared trend component. Differentiating with respect to y_t^{τ} and setting the derivative equal to zero results in the following first-order condition:

$$-2(y_t - y_t^{\tau}) + 2\lambda(L^2 - 4L^{-1} + 6I - 4L + L^2)y_t^{\tau} \tag{6}$$

When we solve this for y_t we obtain:

$$y_t = \lambda(L^2 - 4L^{-1} + 6I - 4L + L^2)y_t^{\tau} + y_t^{\tau} \tag{7}$$

When this expression is solved for all t by defining the trend component, y_t^{τ} as a $t \times 1$ vector containing the trend estimates and y_t as the observed data of the same dimension, the equation above becomes:

$$y_t = (\lambda F + I_t)y_t^{\tau} \tag{8}$$

where F is a $t \times t$ pentadiagonal matrix:

$$F = \begin{bmatrix} 1 & -2 & 1 & 0 & \dots & & 0 \\ -2 & 5 & -4 & \ddots & & & 0 \\ 1 & -4 & 6 & -4 & \ddots & & \vdots \\ 0 & \ddots & \ddots & \ddots & \ddots & & \\ \vdots & & \ddots & \ddots & 6 & -4 & 1 \\ 0 & & & & -4 & 5 & -2 \\ 0 & \dots & & \ddots & 1 & -2 & 1 \end{bmatrix} \tag{9}$$

Solving equation 8 for the trend component, y_t^τ we end up with the HP estimate of the trend:

$$y_t^\tau = (I_t + \lambda F)^{-1} y_t \tag{10}$$

From equation 10, it is clear that by construction the estimates of the permanent, or the trend component y_t^τ at each t, is a weighted average all of the sample observations y. As in any non-stationary I(1) series, the estimated permanent component at time t, y_t^τ can be written as the weighted average of the data. The weights $\psi_\pm$ can also be constant, which would not change the argument.

$$= \sum_{t=1}^{T} \psi_{\pm j,t}(y_t + \Delta_j y_{t\pm j}) \tag{11}$$

$$= \sum_{t=1}^{T} \psi_{\pm j,t} y_t + \sum_{t=1}^{T} \psi_{\pm j,t} \Delta_j y_{t\pm j} \tag{12}$$

From equation (12), one can calculate the cyclical component, y_t^C as a function of the weights and the data:

$$y_t^C = y_t - y_t^\tau = (y_t - \sum_{t=1}^{T} \psi_{\pm j,t} y_t - \sum_{t=1}^{T} \psi_{\pm j,t} \Delta_j y_{t\pm j}) \tag{13}$$

If y_t^C were to be a transitory component, then $\sum_{t=1}^{T} \psi_{\pm j,t} = 1$ indeed. This weighted average representation could be characterised by the following:

$$y_t^\tau = \sum_{j=0}^{m} \psi_{\pm j,t} y_{t\pm j} \tag{14}$$

where $\psi_{\pm j}$ are weights.

The choice of the smoothing parameter, λ, which is the weight attached to the smoothness of evolution of the trend growth component $(\Delta y_{t+1}^\tau - \Delta y_t^\tau)^2$ relative to the cyclical component $(y_t - y_t^\tau)^2$, will have implications for the overall weights: $\psi_{\pm j} = (I_t + \lambda F)^{-1}$. In the weights, parameter λ is the only component that could vary.[8] In a sample from 1 to T, the weights around the mid-point of the sample are constant. However, between the mid-sample and end-of sample, weights change considerably (St-Amant and Norden (1997)).[9]

We have shown that the smoothing parameter, λ influences the weights and speed at which those weights die out in estimation of the permanent component. Figures 3 and 4 show the weights for one-sided and two-sided filters as λ changes. As λ increases, the weights get flatter. In other words, as λ increases, the filter attaches relatively equal weights to different observations. This is the case for both one-sided and two-sided filters. In addition, as λ increases, the lags that enter into the trend estimates die off more slowly. Therefore, the estimates of the trend are more and more influenced by earlier observations in the sample.

Since, with $\lambda = 400,000$, the estimated trends attach high weights to past information, the first order serial correlation in the estimated gap is highly persistent, and is close to or indistinguishable from a unit root.[10] This runs counter to the original reasoning of Borio and Lowe (2004), who chose $= 400,000$ to ensure 'mean reversion' in the estimated gap component.

[8] Unlike a filter like the Henderson filter, the weights vary with time.
[9] For a more recent treatment of the role of the weights see Kulish and Pagan (2019), and Pagan (2017).
[10] Unit root tests are available upon request.

Figure 3
End of Sample Weights

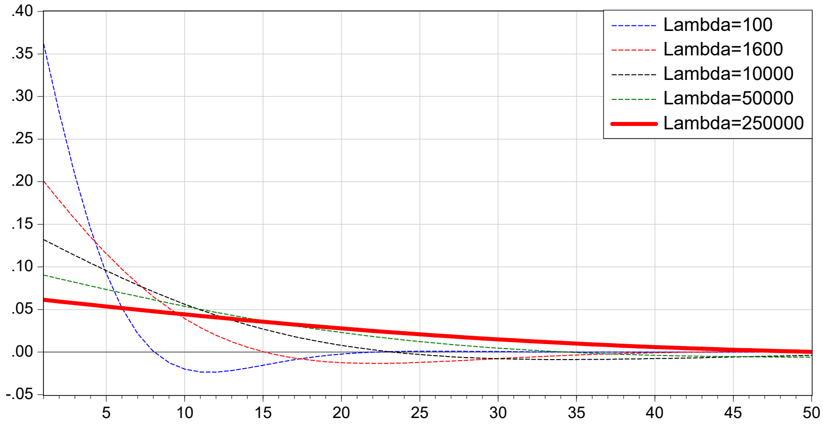


Figure 4
Mid-Sample Weights

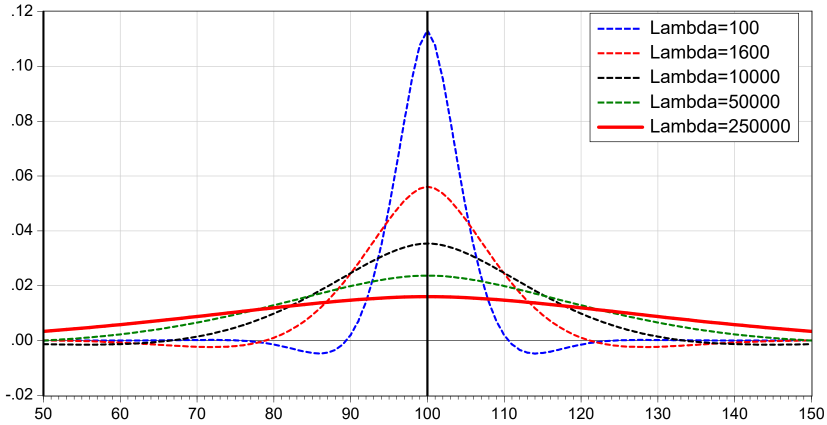


Figure 5
Weights with $\lambda = 400000$

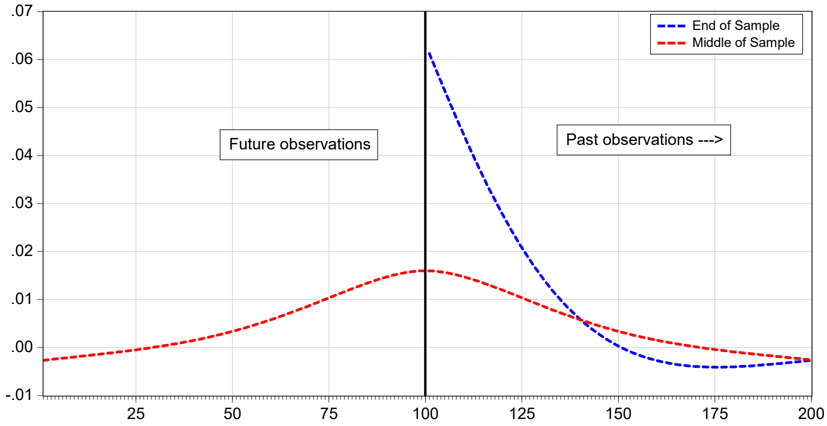


Figure 5 shows HP filter weights with λ = 400,000 for one-sided and two-sided filters. In the two-sided filter, the weight attached to the latest observation is 1.6%. However, the last observation receives a 6.1% weight in the one-sided filter. In the two-sided filter, the weights go to zero for observations from around 55. In other words, observations $t - 55 - j$ where $j > 0$ all receive weights equal to what the trend level is at the end of the sample. However, the weights approach zero more quickly with the one-sided filter, around 40 observations (quarters). Compared with the weights the policymakers would have attached to the last observations, had they had future data, with the one-sided filter they end up attaching significantly more weight to the last observation.

4. Narrative Evidence: Problems of Extreme Events or Changes

As we have observed, the construction of the trend estimate with a one-sided HP filter is essentially averaging past data. In long samples, if the trend is growing at a constant rate, this assumption would not be problematic. But if there are sudden and large changes (such as deep recessions, very strong booms or other disruptions) we may query whether these should be included in the computation of the trend thereafter.

We will be using the financial crisis as our laboratory. Our conjecture is as follows: If financial crises are partly due to large credit expansions, the credit expansion during the build up period should not be an indicator of where the trend lies after the crisis. In other words, post financial crisis periods are associated with a new regime, meaning the trend level of credit growth is perhaps lower. We will be showing that the one-sided HP filter with $\lambda = 400,000$ is problematic in these cases. We will provide narrative evidence from Argentina and Malaysia but the issue applies more generally. In section 4.1, we provide some brief discussion from a number of other countries, including Indonesia, the United States, Ireland, and Greece, which also experienced financial crises in 1997, 2010, 2010 and 2008 respectively.

Argentina 2001-2002

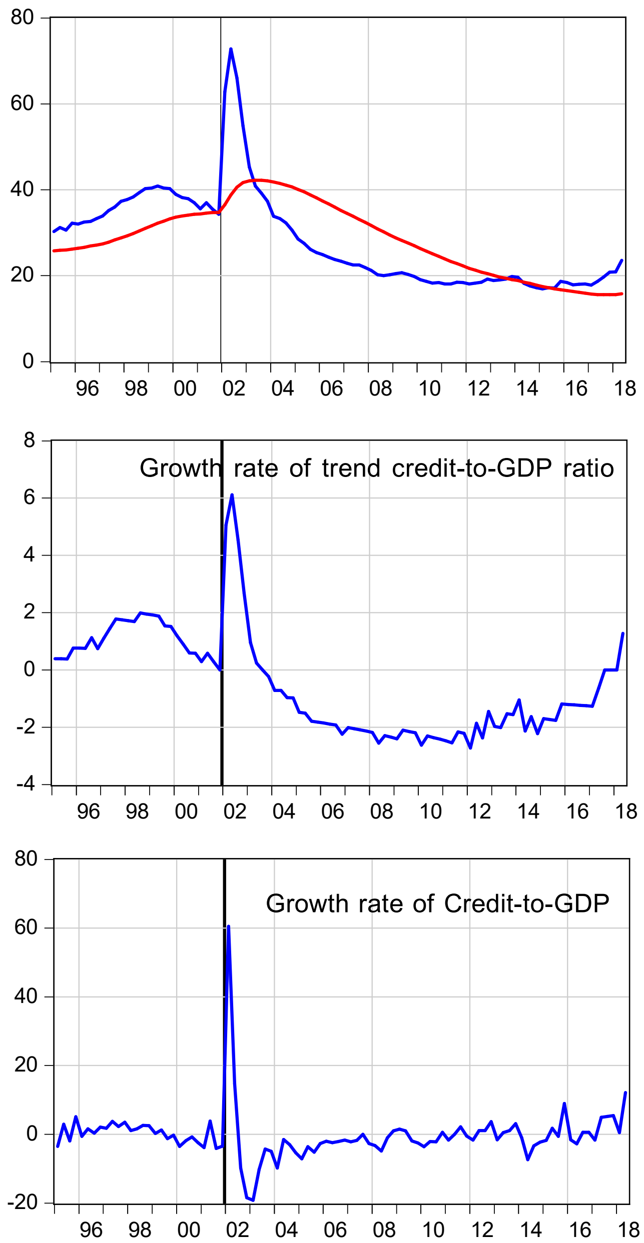
Argentina faced a big currency crisis in 2000-2001, following which it was forced to float its currency. Its GDP collapsed in the following year, the impact of which we observe on the credit-to-GDP ratio (Figure 6). The credit-to-GDP ratio spiked from 34% in 2001Q1 to 73% in 2002Q2. The ratio never recovered to the levels seen in the 1990s. However, the trend estimates did not catch up with the realities of the 'post 2001-crisis' until way into late the 2000s - early 2010s. Interestingly, the credit-to-GDP ratio 'trend' estimates accelerated in the 2001Q1 - 2002Q2 period, even though the country was in a deep crisis. This was partly due to the large and sudden fall in GDP (denominator).

In the post-crisis period, the actual growth rate of credit-to-GDP was in negative territory for almost a decade (bottom panel). However, this fact is not reflected or captured in the BIS estimates of the trend growth rate of the credit-to-GDP ratio for Argentina (middle panel). Consequently, the level of the trend credit-to-GDP ratio remained very strong well into the 2000s, reflecting the earlier strong observations from the pre-crisis period (as well as the large spike during the crisis).

Malaysia around the Asian Financial Crisis

Our second example concerns the Malaysian economy. We examine the Malaysian credit-to-GDP series around the Asian Financial Crisis. When the crisis hit Malaysia in 1997Q3, credit-to-GDP growth was averaging around 4 percent over the previous few years collapsed, and averaged below zero for the next decade (Figure 7, bottom panel). This suggests that the country was now in a 'new regime' in terms of credit conditions and credit growth. However,

Figure 6
Argentina: Credit-to-GDP Actual and Trend



as the middle panel shows, the estimates of the trend growth rate of the credit-to-GDP ratio fell below zero only five years later. In other words, the trend growth rate estimates remained very high for a long time as the influence of the pre-crisis observations remained in the post-crisis trend estimates.

The credit-to-GDP trend that started accelerating in 1996 continued its acceleration well into 2000, even though the country was in a severe financial crisis, and the actual data were in negative territory, as we discussed earlier. Arguably, the rapid increase in the credit-to GDP ratio from the pre-crisis period influenced the trend estimates for the next decade and a half. It was only around 2012 that the level of the trend estimated returned to where it was in 1996. All these different country experiences suggest that the filter used in the BIS analysis has some important implications when a country experiences a sudden regime change.

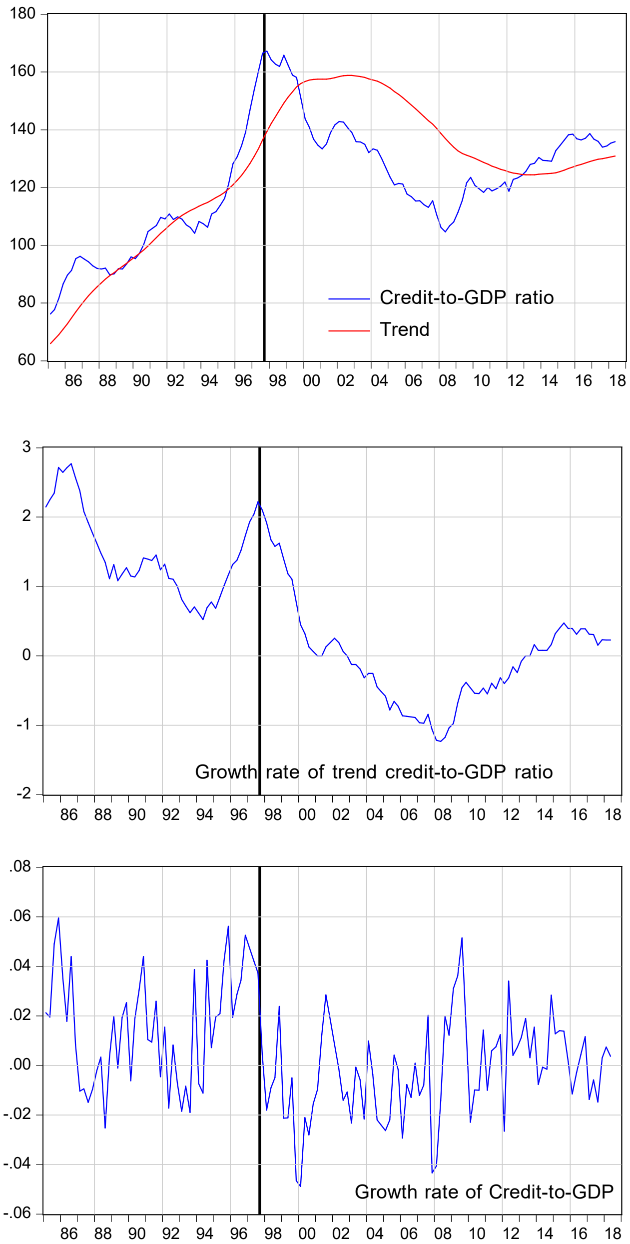
4.1 Evidence from Other Countries

To support our point on the estimated credit gaps, we use evidence from two additional countries: Indonesia and the United States, which experienced financial crises in 1997 and 2008 respectively.

Indonesia 1997-1998

Indonesia's credit-to GDP ratio increased gradually from around 20 percent in 1980 to 66 percent by 1997Q2. By 1998Q2, the ratio reached 129.5 percent, and reversed back to 36 percent in the next four quarters. The sharpest increase in credit-to-GDP ratio from 98.7 to 129.5 occured in 1998Q2, largely due to the devaluation of the currency. In 1998Q3, the ratio reversed back to the level in 1992Q3. This sudden and very sharp increase in the credit-to-GDP ratio was partly due to the large fall in output as the crisis hit the country. However, the sharp increase in the four quarters between 1997Q2 and 1998Q2 continued to influence the trend estimates for almost twelve years. The credit-to-GDP gap in Indonesia only returned to positive territory in mid-2010.

Figure 7
Malaysia around the Asian Financial Crisis



United States 2008-2009

According to the estimates, the US credit-to GDP ratio gap went into negative territory in 2010Q2. Consistent with other countries the very high credit-to-GDP ratio was dominating the trend estimates in the extended period thereafter. If the run up to the crisis in 2007-2008 was partly due to the credit expansion, the data from that period should have no bearing on the estimation of trends post-crisis. However, this is not the case.

5. Conclusions

The credit-to-GDP gaps estimates based on a one-sided HP filter with a smoothing parameter of 400,000, proposed by the Basel Committee are often cited and used in thinking about the counter-cyclical capital buffer calculations. We use the weighted average representation of the same Hodrick-Prescott filter proposed by the Basel Committee and examine the implications of the weights in the estimation of trend, and hence the gaps. We show that the HP filter with a smoothing parameter of 400,000 attaches larger weight to data from the more distant past, relative to a filter with a smaller smoothing parameter. We use a narrative approach to highlight the implications of such weighting schemes. We examine the behaviour of the trend estimates around financial crises, where the change in the environment is very marked and distinct. When there are important 'regime changes', this weighing scheme leads to an important undesirable property: a data-point belonging to an earlier regime continues to influence the trend estimates for around a decade to come. We find that up to 56 quarters of the lags of the series are used to produce the one-sided Hodrick-Prescott trend estimates (and therefore the gap). This potentially makes the first order serial correlation in the estimated gap very persistent and therefore the estimated gaps, which are meant to be stationary/transitory, may be indistinguishable from a unit root.

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