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On the credit-to-GDP gap and spurious medium-term cycles

Yves Schüler

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Non-technical summary

Research question

The Basel Committee on Banking Supervision recommends deploying the countercyclical capital buffer to dampen the risks stemming from excessive lending. To guide the setting of the countercyclical capital buffer, Basel III advises using a reference indicator at the country level: the credit-to-GDP gap. In this paper, I ask whether the methodology used to construct the credit-to-GDP gap – the one-sided Hodrick-Prescott filter (HP1s) – determines the characteristics of the credit-to-GDP gap.

Contribution

HP1s is a real-time version of the regular, two-sided Hodrick-Prescott filter (HP2s). A range of studies shows that HP2s may induce spurious cycles. More specifically, HP2s may create artificial boom-bust cycles in certain settings. I show that also HP1s may induce spurious cycles, particularly pointing out the form of spurious cycles under the Basel III specification of HP1s. Moreover, I contribute by assessing whether the credit-to-GDP gap is subject to such spurious cycles.

Results

Two key results emerge. First, I discover that HP1s under the Basel III specification may induce spurious cycles at medium-term frequencies, i.e. cycles with a maximum duration of around 40 years. Second, I find evidence suggesting that the properties of the credit-to-GDP gap are determined by spurious medium-term cycles. This may impair its usefulness as a reference indicator.

Nichttechnische Zusammenfassung

Fragestellung

Der Basler Ausschuss für Bankenaufsicht empfiehlt die Verwendung des antizyklischen Kapitalpuffers. Dieser soll die Risiken aus einer übermäßigen Kreditvergabe dämpfen. Zur Festsetzung des antizyklischen Kapitalpuffers wird in Basel III ein Leitindikator auf Länderebene – die Kredit/BIP-Lücke – vorgeschlagen. In dieser Studie untersuche ich, ob sich die Verwendung des einseitigen Hodrick-Prescott-Filters (HP1s) zur Konstruktion der Kredit/BIP-Lücke auf die Eigenschaften der Kredit/BIP-Lücke auswirkt.

Beitrag

Der HP1s ist eine für die Echtzeitnutzung gebräuchliche Version des regulären, zweiseitigen Hodrick-Prescott-Filters (HP2s). Eine Reihe von Studien zeigt, dass der HP2s künstliche Zyklen erzeugen kann. Demnach kann der HP2s künstliche Auf- und Abschwünge in bestimmten Situationen generieren. Ich zeige zunächst, dass auch der HP1s künstliche Zyklen erzeugt. Dabei arbeite ich die Eigenschaften dieser Zyklen unter der Basel III-Spezifikation des HP1s heraus. Außerdem analysiere ich, inwieweit die Kredit/BIP-Lücke von solchen künstlichen Zyklen bestimmt wird.

Ergebnisse

Meiner Studie sind zwei wesentliche Ergebnisse zu entnehmen: Erstens kann der HP1s unter der Basel III-Spezifikation mittelfristige künstliche Zyklen mit einer maximalen Dauer von etwa 40 Jahren erzeugen. Zweitens finde ich Hinweise darauf, dass solche künstlichen Zyklen die Kredit/BIP-Lücke beeinflussen. Dies kann die Brauchbarkeit der Kredit/BIP-Lücke als Leitindikator beeinträchtigen.

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On the credit-to-GDP gap and spurious medium-term cycles*

Yves Schüler†

Abstract

The Basel III framework advises considering a reference indicator at the country level to guide the setting of the countercyclical capital buffer: the credit-to-GDP gap. In this paper, I provide empirical evidence suggesting that the credit-to-GDP gap is subject to spurious medium-term cycles, i.e. artificial boom-bust cycles with a maximum duration of around 40 years.

Keywords: Basel III, Hodrick-Prescott filter, detrending

JEL classification: C10, E32, E58, G01.

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1 Introduction

The Basel Committee on Banking Supervision recommends deploying the countercyclical capital buffer (CCyB) to dampen the risks stemming from excessive lending (Basel Committee on Banking Supervision (2010)). To guide the setting of the CCyB, Basel III advises using the credit-to-GDP gap. For instance, if the credit-to-GDP gap of one country starts to exceed two percentage points in a boom phase, supervisors should consider activating this country's CCyB.[1]

The purpose of this paper is (i) to illustrate that the method used to construct the credit-to-GDP gap – the one-sided Hodrick and Prescott (1997) filter with a smoothing parameter of 400,000 (HP1s(400,000)) – may induce spurious medium-term cycles and (ii) to provide evidence that the credit-to-GDP gap is subject to these spurious medium-term cycles.

Spurious medium-term cycles can potentially cause supervisors to receive misleading signals regarding the deployment of the CCyB. In parallel, spurious medium-term cycles may imply that empirical analyses of the credit-to-GDP gap uncover spurious correlations. The reason is that a range of studies finds that the duration of credit-to-GDP cycles (or credit cycles) is often shorter than this medium-term period. These cycles vary between shorter and longer phases and tend to differ in duration from one country to the next, sometimes even resembling business cycles (see, for example, Schüler et al. (2015, 2020); Galati et al. (2016); Hiebert et al. (2018); Rünstler and Vlekke (2018); Schüler (2018); Mandler and Scharnagl (2019); Strohsal et al. (2019)). Spurious medium-term cycles mask these features.

2 The one-sided Hodrick-Prescott filter and spurious cycles

HP1s (similar to the regular two-sided Hodrick-Prescott filter (HP2s)) decomposes the time series $y = (y_1, \dots, y_T)'$ into a gap $\psi = (\psi_1, \dots, \psi_T)'$ and a trend $\tau = (\tau_1, \dots, \tau_T)'$:

$$y_t = \tau_t + \psi_t, \tag{1}$$

where T denotes sample size.

[1]Supervisors decide on whether or not to activate the CCyB using what is known as "guided discretion" – an approach which combines a rules-based component with a discretionary component to arrive at an overall assessment of risks. While a variety of indicators and complementary analyses feed into the discretionary component, the rules-based component is based on the reference indicator.

HP1s estimates the trend component by solving the minimisation problem:[2]

$$\widehat{\tau}_{t|t,\lambda} = \arg\min_{\tau_t} \left(\min_{\tau_1,\ldots,\tau_{t-1}} \left(\sum_{s=1}^{t} (y_s - \tau_s)^2 + \lambda \sum_{s=2}^{t-1} (\tau_{s+1} - 2\tau_s + \tau_{s-1})^2 \right) \right). \tag{2}$$

$\widehat{\tau}_{t|t,\lambda}$ denotes the trend estimate for period t that depends on information only up to time period t. Using $\widehat{\psi}_{t|t,\lambda} = y_t - \widehat{\tau}_{t|t,\lambda}$, yields the gap estimate.[3]

λ controls the smoothness of $\widehat{\tau}_{t|t,\lambda}$: the higher its value, the smoother the extracted trend. Basel III suggests setting $\lambda = 400,000$ for constructing the quarterly credit-to-GDP gap.

2.1 Spurious cycles

It is known that HP2s may induce spurious cycles when applied to difference stationary data (Cogley and Nason (1995); Hamilton (2018)). In these cases, the value of the smoothing parameter determines the cyclicality (duration of boom and bust phases) of an extracted gap. This cyclicality may have no basis in the underlying time series.

I use power transfer functions (PTFs) to show that HP1s(400,000) likewise creates spurious cycles when applied to difference stationary data. A PTF summarises how a filter changes the variance of specific cycles of the underlying time series. Let ω denote the frequency of a cycle, measured in radians going from 0 to π.[4] If $\text{PTF}(\omega) > 1$ ($\text{PTF}(\omega) < 1$), the filter increases (decreases) the variance of the cycle with frequency ω of the underlying time series by the factor $\text{PTF}(\omega)$.

In Figure 1, the left (right) column shows the PTF of HP1s(400,000) in large samples (small samples, i.e. for observation $t = 50$).[5] For the quarterly credit-to-GDP gaps across countries, small sample properties of HP1s(400,000) are relevant (see Section 3).

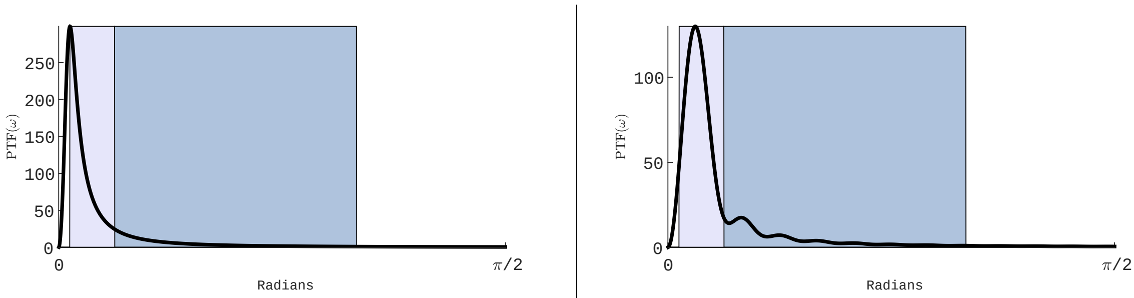
The hump-shaped PTFs show that HP1s(400,000) introduces spurious cycles into an extracted gap. In large samples, the filter strongly amplifies cycles roughly lasting 40 years (left edge of purple (light grey) area) by a factor of up to 300, assuming quarterly data. Such amplification of medium-term fluctuations means that a detrended series may be mainly characterised by this cyclicality. In small samples ($t = 50$ quarters), HP1s(400,000) strongly amplifies cycle frequencies of around 16 years. The factor of amplification is about 130.

[2]HP1s is often implemented by applying HP2s recursively on an expanding sample and keeping, from each recursion step, only the trend/gap estimate for the latest period.

[3]As HP2s uses full sample information, $\widehat{\psi}_{t|T,\lambda}$ and $\widehat{\tau}_{t|T,\lambda}$ denote its gap and trend estimate.

[4]For instance, π denotes the smallest cycle frequency of a length of two quarters, given quarterly data and using the formula $2\pi/\omega$.

[5]I obtain the PTFs as in Wolf et al. (2020).



Large sample ($t = \infty$) Small sample ($t = 50$)

Figure 1: Power transfer functions of HP1s(400,000) when applied to difference stationary data

Notes: The blue (dark grey) area indicates business cycle frequencies (1.5-8 years) and the purple (light grey) area medium-term frequencies (8-40 years), assuming quarterly data.

Table 1: Spurious cycles of HP1s(400,000) for different observations t (in quarters)

t (in quarters)	5	10	25	50	100	150	200	∞
Maximum amplified cycle frequency (in years)	1.4	3.1	8.1	16	32	36	39	40
Factor of amplification	0.5	3.6	30.9	130	304	290	304	300

Notes: Figures refer to applying HP1s(400,000) to difference stationary data.

In Table 1, I show how the maximum amplified cycle duration and factor of amplification increase with t. Around 150 or more observations are required to arrive at a maximum amplified cycle frequency that is fairly close (about 4 years) to the one in large samples.

2.2 What would spurious cycles imply for the properties of the credit-to-GDP gap?

HP1s(400,000) induces spurious cycles into the credit-to-GDP gap if the underlying time series – the quarterly ratio of total credit to the non-financial private sector to GDP – meets two conditions: (i) it is difference stationary and (ii) it has fluctuations at those medium-term frequencies that are amplified.

Assume (a) the underlying time series fulfils both conditions and (b) a maximum sample size of 250 observations (see Section 3). Spurious cycles have the following implications for the properties of the credit-to-GDP gap:

Implication 1: *Fluctuations at medium-term frequencies (8-40 years) contribute most strongly to overall variance.*

Implication 2: *The cycle contributing most strongly to overall variance has a maximum duration of around 40 years.*

Implication 3: *The smaller the sample size, the shorter is the duration of the cycle contributing most strongly to overall variance.*

3 Is the credit-to-GDP gap subject to spurious cycles?

To reject or support the existence of spurious cycles, I analyse whether the estimated spectral densities ($\hat{S}(\omega)$) of all publicly available credit-to-GDP gaps (44 countries) are in line with Implications 1-3.[6] I analyse $\hat{S}(\omega)$ of the credit-to-GDP gaps because Implications 1-3 make claims with regard to cycle frequencies.[7] A spectral density illustrates how the different cycle frequencies contribute to the overall variance of a time series.

The sample sizes differ strongly across countries. The longest sample ranges from 1961Q2 to 2018Q4 (231 observations). The shortest one covers 2009Q1 to 2018Q4 (40 observations). More than 50% of the countries are available starting from 1980Q4.

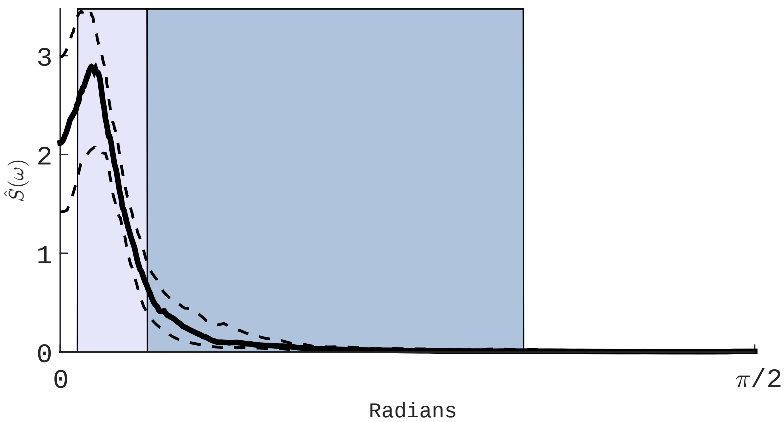


Figure 2: Estimated spectral densities across countries

Notes: The graph illustrates the median (solid line) and the upper/lower quantile (dashed line) of the estimated spectral densities for the 44 credit-to-GDP gaps, scaled by their respective variances. The blue (dark grey) area indicates business cycle frequencies (1.5-8 years), the purple (light grey) area medium-term frequencies (8-40 years).

For **Implication 1**, Figure 2 summarises the distribution of all $\hat{S}(\omega)$. The figure

[6] The data is from the BIS website. Furthermore, I support the analysis of spectral densities by conducting panel unit root tests. The results of the tests point to the existence of spurious cycles. Therefore, the results are in line with the evidence reported in this section. That is, both common and individual unit roots cannot be rejected for the level of the series. For first differences, both common and individual unit roots reject the null of unit root at the 1% level. Results are available upon request.

[7] I estimate the spectral densities using a Parzen window of size $12 \cdot \sqrt{T} + 1$ and scale each spectral density by the variance of the respective series to facilitate a comparison across countries.

indicates that the salient feature of credit-to-GDP gaps across countries is that the most important fluctuations occur at medium-term frequencies (large values of $\hat{S}(\omega)$ in purple (light grey) area).

I consider the maximum value of each gap's $\hat{S}(\omega)$ for Implications 2 and 3 because they make claims about the specific cycle that contributes most strongly to overall variance. I exclude four gaps from these analyses since they have a most important cycle frequency at the duration of ∞, the trend.[8]

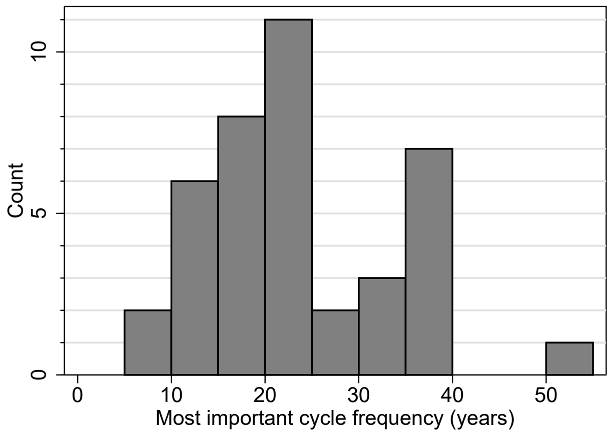


Figure 3: Most important cycle frequencies across countries

Notes: The histogram shows the distribution of the maximum value of the estimated spectral densities across countries.

For **Implication 2**, Figure 3 summarises the most important cycle frequencies in a histogram. It shows that the most important frequency has a maximum duration of around 40 years. Given the non-linear scale of $\hat{S}(\omega)$, 53 years is actually close to 40 years. The mean is 23.6 years. This is in line with the fact that small sample properties of HP1s(400,000) matter for the credit-to-GDP gaps across countries (average sample size ≈ 143) (see Implication 3).

For **Implication 3**, I assess whether a credit-to-GDP gap's most important cycle frequency (y-axis in Figure 4) can be predicted by its sample size (x-axis). Indeed, I find that a smaller sample predicts a shorter most important cycle frequency for the credit-to-GDP gap (dashed line; $R^2 = 0.17$). If the two outliers at the left of the x-axis are excluded, the R^2 rises to 0.35. Furthermore, if I focus on credit-to-GDP gaps with ≤ 150 observations, R^2 increases to 0.64.

Since the properties of the broad set of credit-to-GDP gaps are in line with Implications 1-3, I conclude that there is evidence supporting the existence of spurious medium-term

[8] A visual inspection indicates that these series are driven by a very long cycle rather than a trend. It is known that the estimation of spectral densities cannot discriminate well between longer-term cycle frequencies and the trend.

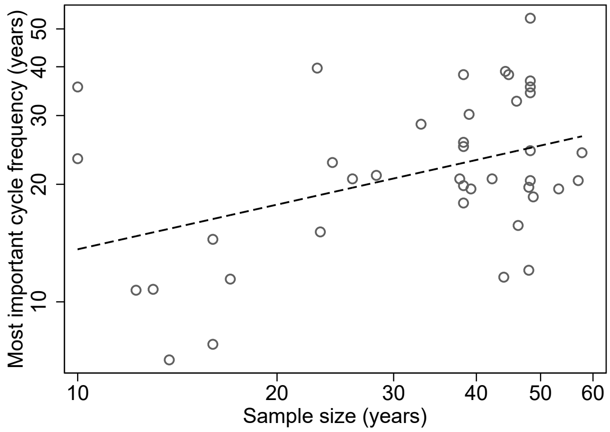


Figure 4: Most important cycle frequency and sample size
Notes: The dashed line refers to the regression line explaining (log of) most important cycle frequency with (log of) sample size.

cycles in the credit-to-GDP gap. Given structural breaks and other empirical irregularities, it is unsurprising that the properties of few credit-to-GDP gaps negate Implications 1-3.

4 Discussion

I present empirical evidence suggesting that the Basel III CCyB reference indicator is subject to spurious medium-term cycles. However, a range of studies finds that the duration of credit-to-GDP cycles differs both over time and across countries (see Galati et al. (2016) and the references therein). Therefore, spurious medium-term cycles may impair the credit-to-GDP gap's use as a reference indicator.

Three policy conclusions follow. First, adhering too rigidly to the reference indicator risks promoting "inaction bias" – the inclination to act too tentatively and thus too late or not at all. That is, the reference indicator might lead to a situation in which supervisors activate the CCyB either too late or not at all ahead of a future financial crisis. This is because there may be cases where the reference indicator is incapable of flagging excessive lending. Second, if financial crises occur at shorter intervals (for instance, at business cycle frequencies), it is unlikely that the reference indicator will flag them going forward. Third, one should consider different methods of detrending when extracting signals from the ratio of credit to GDP. For instance, as a complement to HP1s(400,000), one should use filters that do not induce spurious medium-term cycles, such as difference filters (e.g. multiple-year growth rates) or the Hamilton (2018) filter.

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