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Mind the Basel gap[☆]

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ABSTRACT

The Basel credit gap, the difference between a country's credit-to-GDP ratio and its estimated long-term trend, is used as a basis for setting countercyclical capital buffers under the Basel III regulatory framework. Using international data from the BIS, we show that the Basel credit gap, estimated by a one-sided HP filter, is nearly equivalent to a naive 16-quarter change in the credit-to-GDP ratio and performs equally well in terms of predicting banking crises. We demonstrate that the near-equivalence between deviations from trend and simple changes occurs when the one-sided HP filter is applied to a unit-root process. The goal of this paper is not to evaluate the performance of the Basel credit gap as an early-warning-indicator, but rather to demonstrate that its estimation method is unnecessarily complicated.

1. Introduction

The 2008 financial crisis and it aftermath have given rise to increased emphasis on so-called *macroprudential policy*, aimed at mitigating systemic risks that affect the stability of the entire financial system rather than risks faced by individual financial institutions (See Claessens, 2015; Kahou and Lehar, 2017; Galati and Moessner, 2018, for surveys). Basel III, a regulatory framework agreed upon by the 61 members of the Bank of Settlements (BIS) in 2010, provides guidelines on the implementation of *countercyclical capital buffers*, allowing financial regulators to increase capital requirements for banks during periods of excessive credit growth (Drehmann et al., 2010; Tölö et al., 2018). A key measure considered by regulators when determining countercyclical buffers is the credit gap, often referred to as 'Basel gap': an early warning indicator of financial crises defined as a country's credit-to-GDP ratio in deviation of its long-term trend.[1] Due to its role in setting banking capital requirements, the methodology underlying the credit gap has important real implications. As with any actual-minus-trend gap measure, a crucial step in constructing the credit gap is defining the long-term trend of the credit-to-GDP ratio. The credit gap is calculated following the methodology by Drehmann et al. (2010), who apply a Hodrick and Prescott (1981, 1997) filter recursively to obtain the trend.

We document that the implementation of the one-sided HP filter causes the credit gap to be nearly equivalent to a simple time-series change of the underlying credit-to-GDP ratio. The one-sided HP filter differs from the conventional two-sided filter in

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[1] For example, the European Systemic Risk Board recommends that the benchmark buffer is set at the maximum level of 2.5% when the credit gap is above 10%. The benchmark rate is set at zero when the gap is less than 2%. For gap values between 2% and 10%, the benchmark buffer rate is interpolated between 0% and 2.5% in increments of 0.625%. (Official Journal of the European Union, 2.9.2014, C293). See EBA (2020) and ESRB (2022) for analyses of the implementation of countercyclical buffers and other Basel III policies in the EU during recent years including the COVID-19 pandemic.

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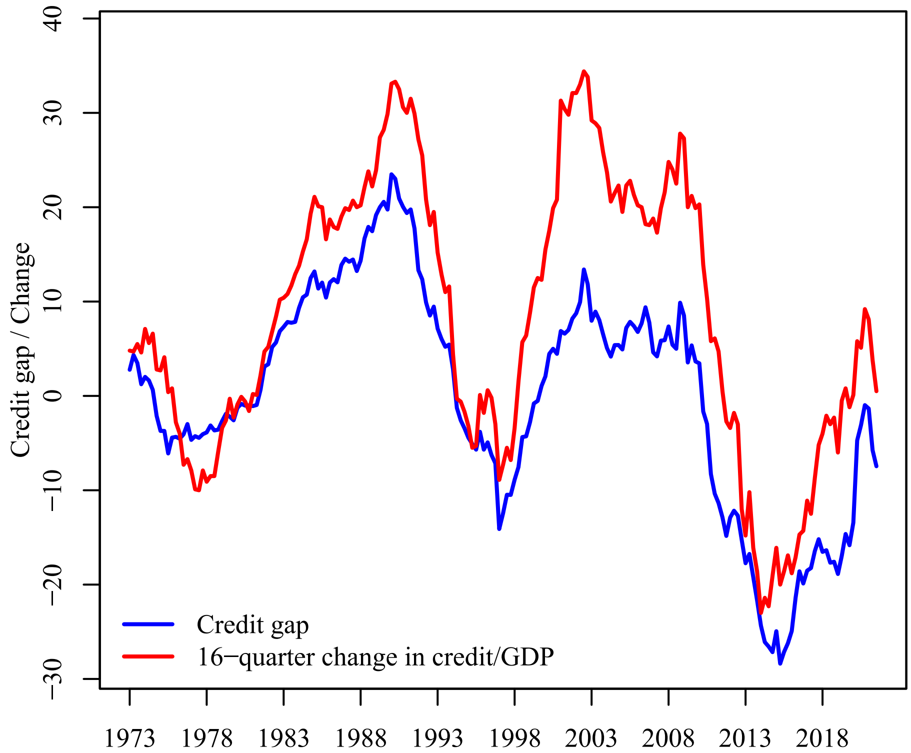

Fig. 1. Credit gap and 16-quarter changes. This figure plots the Basel credit gap (blue line) and the 16-quarter change in the credit-to-GDP ratio (red line) using data for the United Kingdom. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the sense that the trend is re-estimated using the HP filter at each point in time, using only data up to that point in time, such that the recursive (one-sided) trend consists of the endpoints of the real-time trend estimates (Stock and Watson, 1999). We demonstrate that these endpoints mechanically lag the original credit-to-GDP ratio. Applying the analytical expression for the HP filter trend by Cornea-Madeira (2017), we find that deviations from the trend endpoints approximate time-series changes of the original series when applied to an $I(1)$ process. We also show that the near-equivalence between naive changes and the cyclical component estimated by a one-sided HP filter does not apply in general when considering time-series that are integrated at order two or higher ($I(d)$, $d \geq 2$). Earlier studies have also documented concerns regarding the application of the two-sided HP filter to an $I(1)$ process: Cogley and Nason (1995) find that the cyclical component extracted from a unit root process can contain spurious cycles, while King and Rebelo (1993) list second-order integration as one of the necessary conditions for the HP filter to be an optimal linear filter, in the sense of minimizing the mean square error. We find empirically that the credit-to-GDP ratio in almost all of the 44 countries we study indeed resembles an $I(1)$ process, suggesting that the Hodrick–Prescott filter is not the optimal trend estimator in this context.

The close similarity between the estimated credit gap (deviation from trend) and the change in the credit-to-GDP ratio is illustrated below in Fig. 1, using 195 quarterly observations of the credit-to-GDP ratio in the United Kingdom from 1973 to 2021.[2] The credit gap (blue line) is estimated by applying a one-sided HP filter to the credit-to-GDP ratio. The red line shows the simple 16-quarter (4-year) change in the credit-to-GDP ratio. In addition to a high correlation of 0.90, the two series have clearly near-identical cyclical properties in the sense that their peaks and troughs occur simultaneously. This pattern is not specific to the UK: throughout a sample of 43 countries and the Euro area, we find a striking similarity between the credit gap and a naive 16-quarter change in the credit-to-GDP ratio, with an average correlation of 0.91. In addition to our analytical and empirical results, we also conduct a Monte Carlo simulation exercise to confirm the near-equivalence between a recursively estimated deviation from trend and a 16-period change.

As the objective is the identification of credit cycles, the credit gap performs as good (or as bad) as a naive 16-quarter change in the credit-to-GDP ratio. Intuitively, time-series changes and deviations from trend are not necessarily equivalent. It is well possible for a variable to be below (above) trend, even if the variable recently increased (decreased). The credit gap, however, seems to identify changes, rather than actual deviations from trend.

We are not the first to criticize the use of the HP filter. Most notably, Hamilton (2018) argues that the HP filter induces spurious variation into the detrended series and therefore strongly advises against the use of the HP filter in general. Within the context of

[2] The data for the credit-to-GDP ratio is obtained from the Bank of International Settlements (BIS) and available at https://www.bis.org/statistics/c_gaps.htm.

identifying credit cycles, Edge and Meisenzahl (2011) point out sizeable sensitivities of the estimated credit gap to data revisions. Further, Repullo and Saurina Salas (2011), Alessi and Detken (2018), and Afanasyeva (2020) point out that Drehmann et al. (2010) apply the HP filter with a very high value of the smoothing parameter (λ) of 400,000, which causes the estimated trend component to be approximately linear and the resulting credit gap to move too slowly, in particular following periods of negative GDP growth. When the objective is identification of business cycle fluctuations (approximately 2–8 years in duration), it is a common practice with quarterly data to apply the HP filter with a smoothing parameter of 1600. The calibration by Drehmann et al. (2010) is motivated by the observation that credit cycles are approximately four times longer in duration than business cycles. We find, both in actual data and simulations, that the equivalence between credit gaps estimated recursively by the HP filter and by simple changes in the credit-to-GDP ratio holds for both smaller and larger values of the smoothing parameter, with the difference that a higher smoothing parameter generates a gap that approximates a longer difference in the credit-to-GDP ratio.

Drehmann and Juselius (2014) and Drehmann and Yetman (2021) legitimize the use of the credit gap as an early warning indicator, by demonstrating its superior performance in predicting historical banking crises compared to alternative indicators. Using the same set of banking crises as Drehmann and Juselius (2014) and Drehmann and Yetman (2021), we find that the predictive power of the simple 16-quarter change in the credit-to-GDP ratio is nearly equivalent to that of the credit gap. When extending the set of historical crises by allowing for ‘quiet’ crisis episodes that do not coincide with a bank panic, following Baron et al. (2021), the performance of both indicators deteriorates considerably. Nevertheless, we continue to find that the predictive power of the credit gap and simple 16-quarter change are nearly equivalent.

Evaluating whether the Basel credit gap is the optimal early warning indicator is not the ultimate goal of this paper. The methodology of the credit gap is relevant because it is currently used by financial regulators worldwide as a key input for setting countercyclical capital buffers. Our paper aims to raise awareness that the current methodology leads to a credit gap that is nearly equivalent to a 16-quarter change in the credit-to-GDP ratio. The credit gap can thus be calculated in a way that is easier and more transparent. This is not to say that a gap calculated based on either an HP filter or a 16-quarter change are necessarily optimal indicators of systemic risk.

This paper proceeds as follows: in Section 2 we describe the methodology underlying the credit gap and provide analytical results documenting the similarity between the estimated deviation from trend and simple time-series changes. Section 3 provides simulation results, while empirical results for the 44 countries in our sample are reported in Section 4. Section 5 evaluates the performance of both measures in terms of predicting banking crises, and Section 6 concludes.

2. Analytical background

2.1. Credit gap

The credit gap is defined as the credit-to-GDP ratio in deviation of its trend, where the trend is estimated following Hodrick and Prescott (1981, 1997) by minimizing the following objective function:

$$\min_{\tau}\left\{\sum_{t=1}^{T}\left(y_t-\tau_t\right)^2+\lambda\sum_{t=2}^{T-1}\left[\left(\tau_{t+1}-\tau_t\right)-\left(\tau_t-\tau_{t-1}\right)\right]^2\right\} \tag{1}$$

where y_t and τ_t are the credit-to-GDP ratio and its estimated trend in period t, and λ is the smoothing parameter. The objective function is minimized numerically. The *two-sided* HP filter applies (1) to a full time-series sample, resulting in an ex-post estimate of the trend τ_t and gap $\left(y_t-\tau_t\right)$. To facilitate real-time identification of the trend, the HP filter is applied recursively, by at each point T' minimizing the objective function (1) using only data up to point T' and collecting the endpoint of the estimated trend $\tau_{T'}$ and gap $\left(y_{T'}-\tau_{T'}\right)$. This recursive procedure is referred to as the *one-sided* HP filter (Stock and Watson, 1999). Following Drehmann et al. (2010), the credit gap is estimated by applying a one-sided HP filter with a smoothing parameter of $\lambda = 400{,}000$.

Fig. 2 illustrates the estimation of the one-sided HP filter using the UK data on the credit-to-GDP ratio as an example. The black line in Panel A shows the credit-to-GDP ratio from 1973 to 2021. The red line shows the trend estimated by applying a two-sided (full-sample) HP filter with λ equal to 400,000. The estimated full-sample trend runs smoothly through the observed data and describes accurately long-term non-cyclical development of the credit-to-GDP ratio.

The red line, however, is not the trend used for the calculation of the credit gap. Rather, the trend required for obtaining the credit gap is estimated by the so-called one-sided HP filter, which is implemented recursively. To illustrate, the red line in Panel B of Fig. 2 shows the trend component estimated using only data available up to 1989, with the blue dot marking the endpoint. Panel C displays the endpoints of trends estimated using data up to 1989, 2001, 2013, and 2021. The thin red lines in Panel D show all the trends estimated using subsamples of data up to each quarterly observation, while the blue line connects the endpoints of these estimated real-time trend components. This blue line, the recursively-estimated trend, is used for the calculation of the credit gap. It is clearly visible from the figure that, unlike the full-sample or two-sided trend (Panel A), the recursive or one-sided trend (Panel D) strongly resembles a smoothed lagged value of the observed data. This is in particular noticeable from Panel C, which shows clearly that each of the subsample trends crosses the original series close towards the end of the subsample, such that the endpoint of the trend lags the original series.

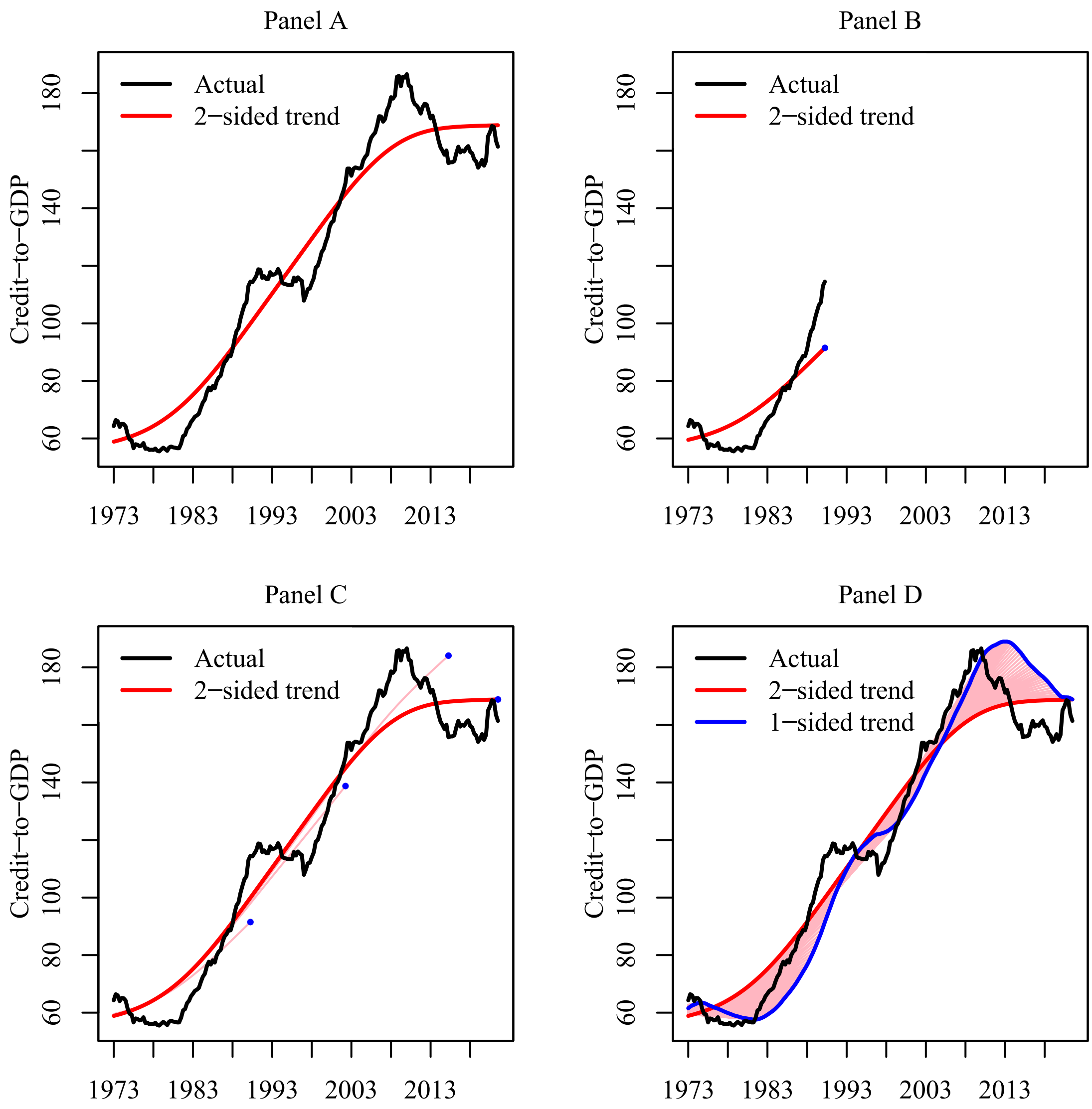

Fig. 2. Two-sided and one-sided trend estimates. Panel A shows the credit-to-GDP ratio (black line) of the United Kingdom and its long-term trend estimated by the two-sided HP filter (red line). Panel B shows the credit-to-GDP ratio and trend estimated using only data up to 1989. Panel C shows trends estimated using data up to 1989, 2001, 2013, and 2021. In Panel D, the red lines depict all Hodrick–Prescott trends estimated at different points in time. The blue line connects the endpoints of the subsample trends, resulting in the recursive or one-sided Hodrick–Prescott trend. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.2. Analytical expressions

Several studies (e.g. Mise et al., 2005; De Jong and Sakarya, 2016; Hamilton, 2018) point out that the HP filter behaves differently at the endpoints of sample. Cornea-Madeira (2017) finds an analytical expression for the endpoints of the trend. The endpoint of the trend τ_T is defined as a weighted average of the T observations of y:

$$\tau_T = \sum_{t=1}^{T} p_t y_t \tag{2}$$

where $\sum_{t=1}^{T} p_t = 1$. Cornea-Madeira (2017) derives analytical expressions for p_t as a function of λ, t, and T. The weights p_t do not depend on the distributional properties of y_t. We apply the results of Cornea-Madeira (2017) to demonstrate that the last observation of an $I(1)$ time-series in deviation of its estimated trend is highly correlated with the last observation of the time-series in deviation of its own lag.[3] Let y_t be an $I(1)$ process, such that

$$y_t = y_{t-1} + \xi_t = \sum_{i=1}^{t} \xi_i, \tag{3}$$

where ξ_t is a stationary process. (Note that we assume $y_0 = 0$, without loss of generality). The endpoint of the HP trend (2) can be expressed as:

$$\begin{aligned} \tau_T &= \sum\nolimits_{t=1}^{T} p_t \sum\nolimits_{i=1}^{t} \xi_i \\ &= \xi_1 \left(p_1 + p_2 + \cdots + p_T\right) + \xi_2 \left(p_2 + \cdots + p_T\right) + \cdots + \xi_T p_T \\ &= \sum\nolimits_{t=1}^{T} \xi_t \sum\nolimits_{j=t}^{T} p_j \\ &= \sum\nolimits_{t=1}^{T} \varphi_t \xi_t, \end{aligned} \tag{4}$$

where $\varphi_t = \sum_{j=t}^{T} p_j$. Given the estimated trend, the endpoint of the cycle (deviation from trend) is expressed as:

$$\begin{aligned} x_T &= y_T - \tau_T \\ &= \sum\nolimits_{t=1}^{T} \xi_t - \sum\nolimits_{t=1}^{T} \varphi_t \xi_t \\ &= \sum\nolimits_{t=1}^{T} \left(1 - \varphi_t\right) \xi_t. \end{aligned} \tag{5}$$

The k-period change, y_T in deviation of its k-order lag, is defined as:

$$\begin{aligned} \Delta_k y_T &= y_T - y_{T-k} \\ &= \sum\nolimits_{t=1}^{T} \xi_t - \sum\nolimits_{t=1}^{T-k} \xi_t \\ &= \sum\nolimits_{t=T-k+1}^{T} \xi_t. \end{aligned} \tag{6}$$

Given the weights p_t (as a function of λ, t, and T; Cornea-Madeira, 2017) and the distribution of ξ_t, we can derive $cor(x_T, \Delta_k y_T)$, for any lag k. For example, if y_t follows a random walk, $\xi_t \sim i.i.d.(0, \sigma^2)$, it can be shown that:[4]

$$cor\left(x_T, \Delta_k y_T\right) = \frac{\sum_{t=T-k+1}^{T} \left(1 - \varphi_t\right)}{\sqrt{k \sum_{t=1}^{T} \left(1 - \varphi_t\right)^2}}. \tag{7}$$

Fig. 3 illustrates these correlations. The red dots in Panel A plot $cor(x_T, \Delta_k y_T)$ for a random walk y_t, with $T = 200$ and $\lambda = 400{,}000$, for $k = 1 \dots 40$. The correlation is maximized at 0.83, for $k = 16$.

The blue dots in Fig. 3 are based on the UK data, indicating the correlation coefficients between the credit gap and changes in the credit-to-GDP ratio, for different lag lengths over which the change is computed.[5] The theoretical correlations in red and the empirical correlations in blue show a very similar pattern, with the correlation between the credit gap and an k-quarter change in the credit-to-GDP ratio being maximized around $k = 16$. In general, the empirical sample correlations are higher than the theoretical population correlations. As we show in Appendix, it is possible to generate higher theoretical correlations when moving beyond a simple random walk, for example by allowing for time-varying volatility. The correlation being maximized around $k = 16$ holds nevertheless across different data generating processes and sample sizes, as demonstrated in Appendix.

The theoretical correlations between changes and deviations from trend $cor(x_T, \Delta_s y_T)$ can be derived only when ξ_t (the first-order change in y_t) is stationary. When y_t is of order of integration two or higher ($I(d)$, $d \geq 2$), the change $\Delta_s y_T$ is no longer stationary, meaning that its population covariance with the trend endpoints is in general not defined. We demonstrate in the next section by simulation that the sample correlations between x_T and $\Delta_s y_T$ are indeed not converging when y_t is an $I(2)$ or $I(3)$ process.

2.3. The role of λ

Repullo and Saurina Salas (2011) and Alessi and Detken (2018) criticize the credit gap methodology for the large calibrated value of the smoothing parameter λ. Typically, the HP filter is applied to identify business cycles, with the smoothing parameter calibrated at $\lambda = 1600$ (Hodrick and Prescott, 1981). Drehmann et al. (2010) find that a smoothing parameter of $\lambda = 400{,}000$ is optimal to identify credit cycles, which are generally longer in duration than business cycles. Repullo and Saurina Salas (2011) and Alessi and Detken (2018) argue that the estimated trend component is approximately linear and the resulting credit gap moves too slowly, in particular following periods of negative GDP growth. In addition, Phillips and Jin (2021) find that the HP filter with high value of λ does not remove stochastic trends when applied to small samples.

Our observation that the one-sided trend mechanically lags the credit-to-GDP ratio is distinct from these concerns regarding the calibration of λ. In fact, we find that the similarity between credit gaps estimated recursively by the one-sided HP filter and by simple changes in the credit-to-GDP ratio holds for different values of the smoothing parameter. For lower values of the smoothing

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[3] Below we show empirically that the credit-to-GDP ratio of most countries resembles an $I(1)$ process.

[4] See Appendix for details.

[5] Note that the red dots of Fig. 3 shows the theoretical correlation for a fixed sample size of $T = 200$. The empirical plot is based on a sample of 195 observations, where the endpoints of the trends and the time-series differences are obtained at every observation $t = 1, \dots, 195$.

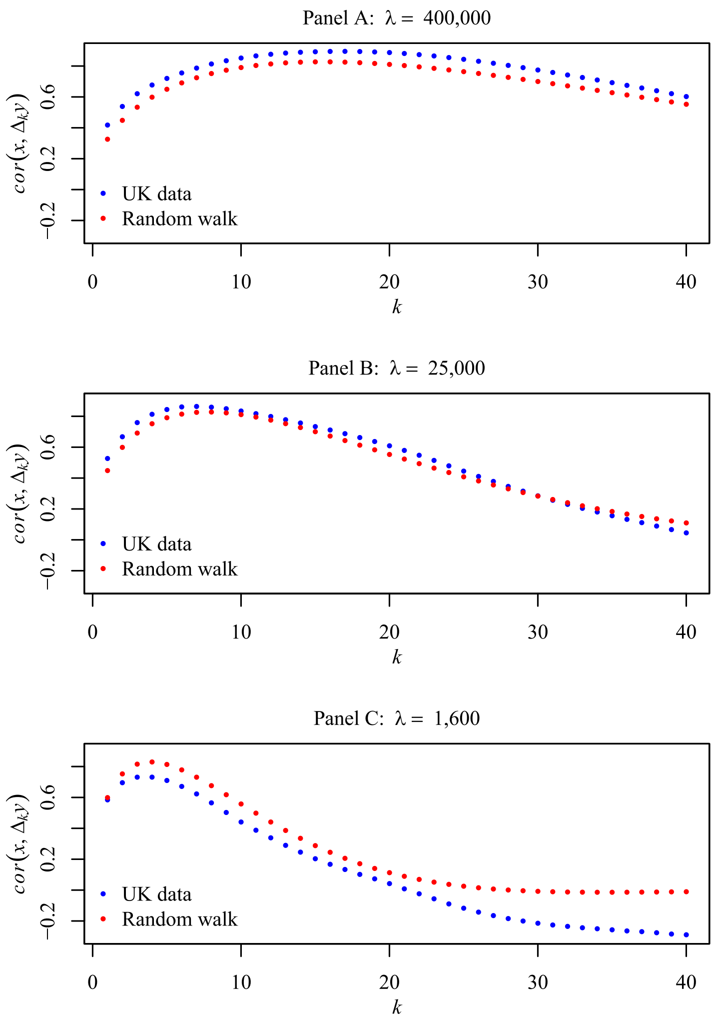

Fig. 3. Correlation between credit gap and simple changes. This figure plots the correlation coefficients between the credit gap ($x_t = y_t - \tau_t$) and changes in the credit-to-GDP ratio ($\Delta_k y_t = y_t - y_{t-k}$). The horizontal axis depicts the number of quarters ($k = 1, \ldots, 40$) over which the change in the credit-to-GDP ratio is calculated. The blue dots represent correlations estimated based on credit-to-GDP data for the UK. The red dots represent correlations based on analytical solutions for random walk credit-to-GDP ratio. The three panels are based on different values of the HP filter smoothing parameter λ. The smoothing parameter is equal to 400,000 in Panel A, 25,000 in Panel B, and 1600 in Panel C. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

parameter, the gap approximates a shorter difference in the credit-to-GDP ratio. We show in Panels B and C of Fig. 3 that the correlation between the endpoint of the trend and the k-period change in a random walk process are also highly correlated when the trend is estimated with a smoothing parameter of $\lambda = 1600$ or $\lambda = 25{,}000$. However, a lower smoothing parameter implies a lower lag k at which the correlation is maximized. The correlation is maximized at $k = 4$ for $\lambda = 1600$ and at $k = 8$ for $\lambda = 25{,}000$.

The blue dots in Fig. 3 show the correlation between changes in the UK credit-to-GDP ratio and deviations from trend estimated by an HP filter with $\lambda = 1600$ and $\lambda = 25{,}000$. Similar to the analytical result, the correlation is maximized at $k = 4$ and $k = 7$, respectively. In Section 3, we conduct a Monte Carlo simulation exercise to further inspect the relation between a gap measure based on one-sided cycles and simple time-series changes, for different values of λ.

3. Simulation results

We next confirm the above analytical results with simple Monte Carlo simulations. The results of the simulations are presented in Fig. 4. As a benchmark case, we simulate a random sample ($T = 200$) of the credit-to-GDP ratio following a random walk, calculate the credit gap, and correlate the gap measure with simple time series changes of the credit-to-GDP ratio. We repeat this 1000 times. Panel A of the figure plots the median as well as the 10th, 25th, 75th, and 90th percentiles of the correlation coefficients between the credit gaps and the time series changes, for different change periods (k). As the analytical correlations presented in Panel A

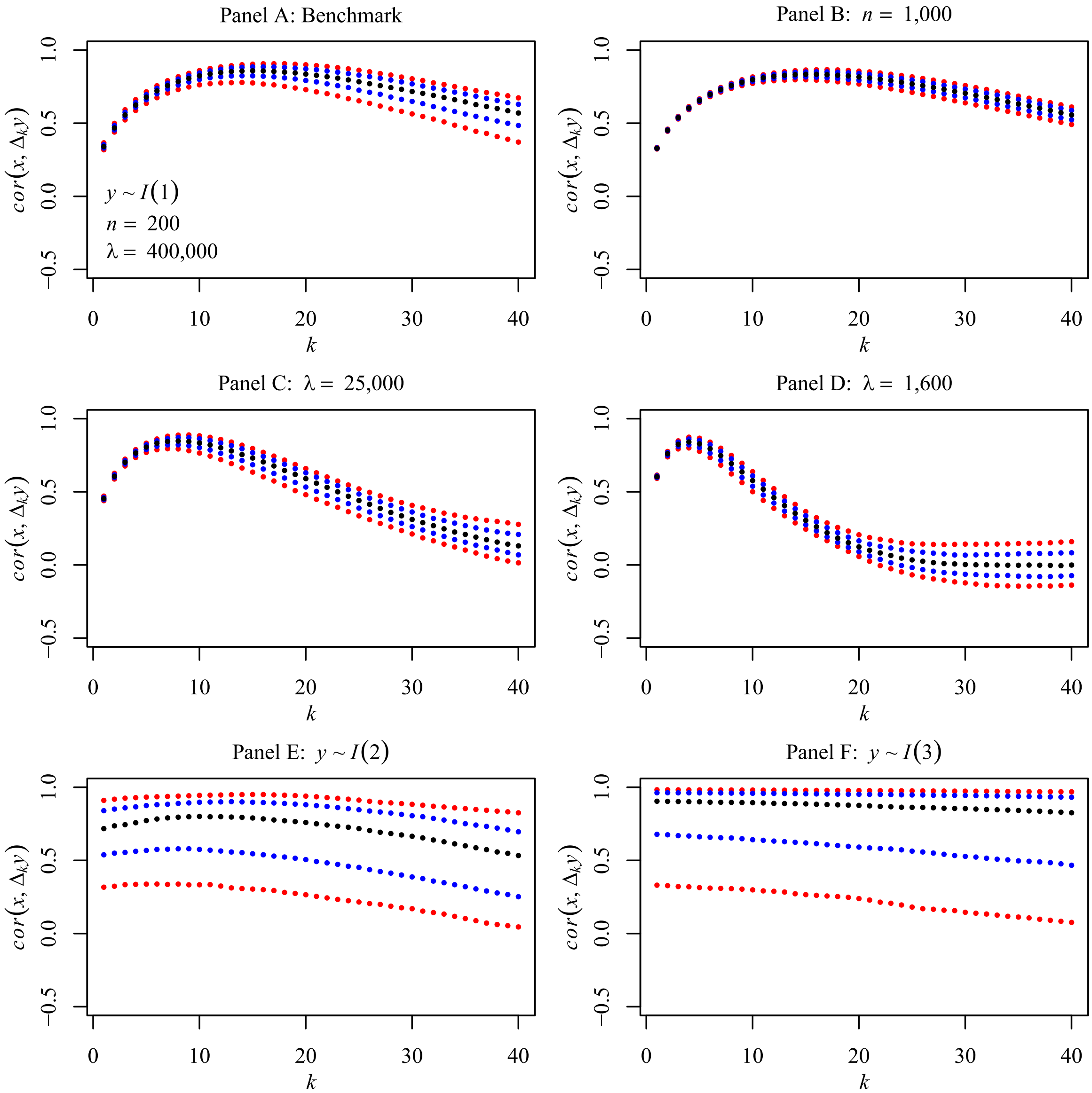

Fig. 4. Simulation results. This figure plots percentiles of the correlation coefficients between the credit gap ($x_t = y_t - \tau_t$) and changes in the credit-to-GDP ratio ($\Delta_k y_t = y_t - y_{t-k}$) based on Monte Carlo simulations with 1000 replications. The horizontal axis depicts the number of quarters ($k = 1, \ldots, 40$) over which the change in the credit-to-GDP ratio is calculated. The red dots represent the 10th and the 90th percentile of the correlation coefficients, the blue dots represent the 25th and the 75th percentiles, and the black dots represent the median. Panel A represents a benchmark where y_t follows an $I(1)$ process ($\Delta y_t \sim N(0,1)$), $\lambda = 400{,}000$ and sample size equals $n = 200$. The other panels change one of these parameters. Panel B is based on a longer time series ($n = 1000$) and Panels C and D are based on smaller smoothing parameters ($\lambda = 25{,}000$ and $\lambda = 1600$, respectively). In Panel E y_t follows an $I(2)$ process ($\Delta^2 y_t \sim N(0,1)$) and in Panel F an $I(3)$ process ($\Delta^3 y_t \sim N(0,1)$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

of Fig. 3, the median simulation-based correlation reaches its highest value, 0.86, at $k = 16$. Notably, the range of correlations is narrow: The 10th percentile of the correlation at $k = 16$ is 0.77 and the 90th percentile is 0.90. This narrow range of the correlations indicates that when the credit-to-GDP ratio follows an $I(1)$ process, one should expect the correlation between the credit gap and the changes in the credit ratio to always follow the same pattern.

The remaining panels of Fig. 4 provide variations of the benchmark case. First, in Panel B we simulate $T = 1000$ observations of the credit ratio, rather than $T = 200$ in Panel A. As the results in Panel B are practically identical to Panel A, we conclude that the sample size does not affect the correlation between the credit gap and the change in credit-to-GDP ratio. In Panels C and D we study the effects of changing the HP filter's smoothing parameter. In Panel C we use $\lambda = 25{,}000$ and in Panel D $\lambda = 1600$. As in the analytical results above, a lower λ results in the credit gap correlating more strongly with a shorter change in the credit-to-GDP

Table 1
Data. This table presents the quarterly credit-to-GDP ratio data used in the empirical analyses of this paper for 43 countries and the Euro area. *Start* gives the date of the first observation, data for all countries ends in 2021-Q3. *Obs* gives the total number of quarterly observations per country. The data are from the Bank for International Settlements.

Country		Start	Obs	Country		Start	Obs
AR	Argentina	1984-Q4	148	IL	Israel	1990-Q4	124
AT	Austria	1960-Q4	244	IN	India	1951-Q2	282
AU	Australia	1960-Q2	246	IT	Italy	1960-Q4	244
BE	Belgium	1970-Q4	204	JP	Japan	1964-Q4	228
BR	Brazil	1996-Q1	103	KR	Korea	1962-Q4	236
CA	Canada	1955-Q4	264	LU	Luxembourg	1995-Q1	107
CH	Switzerland	1960-Q4	244	MX	Mexico	1980-Q4	164
CL	Chile	1983-Q1	155	MY	Malaysia	1964-Q2	230
CN	China	1985-Q4	144	NL	Netherlands	1961-Q1	243
CO	Colombia	1996-Q4	100	NO	Norway	1960-Q4	244
CZ	Czech Republic	1993-Q1	115	NZ	New Zealand	1960-Q4	244
DE	Germany	1960-Q4	244	PL	Poland	1992-Q1	119
DK	Denmark	1966-Q4	220	PT	Portugal	1960-Q4	244
ES	Spain	1970-Q1	207	RU	Russia	1995-Q2	106
FI	Finland	1970-Q4	204	SA	Saudi Arabia	1993-Q1	115
FR	France	1969-Q4	208	SE	Sweden	1961-Q1	243
GB	United Kingdom	1963-Q1	235	SG	Singapore	1970-Q4	204
GR	Greece	1970-Q4	204	TH	Thailand	1970-Q4	204
HK	Hong Kong SAR	1978-Q4	172	TR	Turkey	1986-Q1	143
HU	Hungary	1970-Q4	204	US	United States	1947-Q4	296
ID	Indonesia	1976-Q1	183	ZA	South Africa	1965-Q1	227
IE	Ireland	1971-Q2	202	XM	Euro area	1999-Q1	91

ratio. The correlation is maximized at $k = 8$ for $\lambda = 25{,}000$ and at $k = 4$ for $\lambda = 1600$. For the lower smoothing parameters, the range of simulated correlations is also very narrow.

Finally, Panels E and F show that the close systematic relation between the credit gap and changes in the credit ratio breaks down when the credit-to-GDP ratio has order of integration higher than one. In Panel E, we let the simulated credit-to-GDP ratio follow an $I(2)$ process, such that the change $\Delta_s y_T$ is not stationary. While the simulated sample correlations between the credit gap and changes in the credit ratio are still relatively high, the range of correlations is very wide compared to Panel A. The median correlation reaches its maximum, 0.80, at $k = 10$. With $k = 10$, the 10th percentile is 0.35 and the 90th percentile 0.94. This implies that in some simulation runs based on an $I(2)$ process, the credit gap is highly correlated with a 10-quarter changes in the credit-to-GDP ratio and in other runs the correlation is rather low. Panel F shows that similar results are obtained when the credit-to-GDP follows an $I(3)$ process.

Overall, the Monte Carlo simulations confirm our analytical results. When the underlying data follows an $I(1)$ process, an actual-minus-trend gap measure based on a one-sided HP filter is mechanically highly correlated with a simple change in the underlying data. This result is independent of the sample size, and the smoothing parameter merely affects how long a change in the underlying data the gap measure emulates. This relation breaks down when the order of integration of the underlying data is higher than one.

4. Empirical results

In this section, we show that the similarity between the credit gap and the 16-quarter difference in the credit ratio holds for a large sample of countries. For the empirical analyses we use quarterly credit-to-GDP data for 43 countries and the Euro area from the Bank for International Settlements.[6] The data start at different points in time for different countries with the earliest time series extending back to the late 1940's and early 1950's. Data for all countries ends in 2021-Q3. Table 1 lists the countries in our sample and the periods for which we observe the quarterly credit-to-GDP ratios.

We begin by analyzing the order of integration of the data. As we show analytically and through simulations above, the close mechanical similarity between the credit gap and the 16-quarter change in the credit-to-GDP ratio relies on the credit ratio following an $I(1)$ process. Hence, we first establish that the real world credit-to-GDP ratios are indeed integrated of order one. In Table 2, we report for each country the test statistic and p-value of an Augmented Dickey–Fuller (ADF) test applied to the level of the credit-to-GDP ratio (y_t). For each country, we consider one test where we set the number of lags equal to 4, and one test were the number of lags is selected by maximizing Akaike's information criterion (AIC). In both cases, we are not able to reject the null hypothesis of a unit root, at 5% significance levels for all countries except Argentina. We also report the results of a panel unit root test, specifically the Z-test by Choi (2001), which pools the observations across all 43 countries (excluding the Euro area aggregate).[7] Also utilizing the increased statistical power of the full panel, we cannot reject a unit root in the credit-to-GDP ratio.

[6] The data are available for download at https://www.bis.org/statistics/c_gaps.htm.

[7] The Z-test by Choi (2001) is implemented as the function "purtest" in the "PLM" package in R (Croissant and Millo, 2008; R Core Team, 2022).

Table 2
Level stationarity tests. This table present the results of testing for stationarity of the levels of the credit-to-GDP ratios. Columns marked $k = 4$ present the test statistic (ADF) and p-values (p) of the Augmented Dickey–Fuller test using four lags. The columns marked AIC present the test statistic and p-values for the Augmented Dickey–Fuller test where the lag length is chosen to optimize the Akaike Information Criterion. The data is on a quarterly frequency, sample periods and sizes are given in Table 1.

	$k = 4$		AIC			$k = 4$		AIC	
	ADF	p	ADF	p		ADF	p	ADF	p
AR	−3.235	0.020	−3.804	0.004	IN	−0.853	0.802	−1.044	0.738
AT	−1.151	0.696	−1.141	0.700	IT	−1.074	0.726	−1.093	0.719
AU	−0.873	0.796	−0.686	0.847	JP	−1.564	0.499	−1.849	0.356
BE	−0.086	0.948	−0.345	0.914	KR	−0.333	0.916	−0.494	0.889
BR	0.997	0.996	1.344	0.999	LU	−1.247	0.652	−1.204	0.670
CA	1.611	1.000	1.395	0.999	MX	−2.805	0.060	−2.093	0.248
CH	1.030	0.997	1.715	1.000	MY	−1.331	0.615	−1.390	0.587
CL	−0.559	0.875	−0.007	0.956	NL	−1.303	0.628	−1.340	0.611
CN	0.384	0.982	0.569	0.988	NO	−0.766	0.826	−0.526	0.882
CO	−1.063	0.728	−0.804	0.813	NZ	−0.846	0.804	−0.962	0.767
CZ	−1.246	0.652	−0.873	0.793	PL	−1.073	0.725	−1.278	0.638
DE	−1.841	0.360	−1.955	0.307	PT	−1.700	0.430	−1.523	0.520
DK	−0.821	0.811	−0.737	0.834	RU	−0.746	0.829	−0.749	0.828
ES	−1.237	0.658	−1.073	0.726	SA	−0.517	0.883	−0.776	0.821
FI	−0.573	0.873	−0.510	0.885	SE	0.374	0.981	0.932	0.996
FR	2.562	1.000	2.531	1.000	SG	−0.535	0.880	−0.284	0.924
GB	−0.679	0.849	−0.387	0.908	TH	−1.702	0.429	−1.626	0.467
GR	−0.344	0.915	−0.743	0.832	TR	0.585	0.989	0.171	0.970
HK	1.071	0.997	2.188	1.000	US	−1.463	0.551	−1.094	0.719
HU	−1.086	0.721	−1.750	0.404	ZA	−1.376	0.594	−1.382	0.591
ID	−2.094	0.248	−2.777	0.064	XM	−2.128	0.234	−2.210	0.204
IE	−0.913	0.783	−0.896	0.788					
IL	−2.411	0.141	−2.837	0.056	Panel	5.633	1.000	5.587	1.000

Table 3
Difference stationarity tests. This table present the results of testing for stationarity of the changes of the credit-to-GDP ratios. Columns marked $AR(4)$ present the estimates of the autoregressive terms of $AR(4)$ models of the changes in credit-to-DGP ratios. Columns marked $k = 4$ presents the test statistic (ADF) and p-values (p) of the Augmented Dickey–Fuller test using four lags. The columns marked AIC present the test statistic and p-values for the Augmented Dickey–Fuller test where the lag length is chosen to optimize the Akaike Information Criterion. The data is on a quarterly frequency, sample periods and sizes are given in Table 1.

	$k = 4$		AIC			$k = 4$		AIC	
	ADF	p	ADF	p		ADF	p	ADF	p
AR	−6.961	0.000	−6.694	0.000	IN	−4.608	0.000	−2.988	0.037
AT	−6.119	0.000	−4.265	0.001	IT	−4.563	0.000	−2.995	0.037
AU	−4.056	0.001	−3.914	0.002	JP	−4.403	0.000	−3.023	0.034
BE	−5.301	0.000	−6.598	0.000	KR	−4.865	0.000	−6.277	0.000
BR	−3.918	0.003	−9.508	0.000	LU	−4.849	0.000	−6.221	0.000
CA	−6.878	0.000	−8.121	0.000	MX	−4.211	0.001	−4.634	0.000
CH	−5.970	0.000	−8.292	0.000	MY	−5.054	0.000	−6.324	0.000
CL	−4.714	0.000	−8.349	0.000	NL	−4.756	0.000	−3.353	0.014
CN	−5.046	0.000	−4.064	0.002	NO	−5.500	0.000	−6.245	0.000
CO	−3.555	0.009	−4.711	0.000	NZ	−4.872	0.000	−3.669	0.005
CZ	−4.420	0.000	−8.494	0.000	PL	−2.983	0.040	−2.998	0.038
DE	−5.698	0.000	−4.042	0.001	PT	−3.892	0.002	−3.162	0.024
DK	−4.502	0.000	−3.160	0.024	RU	−4.508	0.000	−7.737	0.000
ES	−3.039	0.033	−2.073	0.256	SA	−4.661	0.000	−5.538	0.000
FI	−5.052	0.000	−8.096	0.000	SE	−5.147	0.000	−5.071	0.000
FR	−5.576	0.000	−3.274	0.017	SG	−5.416	0.000	−4.853	0.000
GB	−4.664	0.000	−4.906	0.000	TH	−3.399	0.012	−3.537	0.008
GR	−4.587	0.000	−2.170	0.218	TR	−5.841	0.000	−2.777	0.064
HK	−5.134	0.000	−6.120	0.000	US	−5.912	0.000	−4.032	0.001
HU	−3.339	0.014	−3.005	0.036	ZA	−5.781	0.000	−6.207	0.000
ID	−6.296	0.000	−6.280	0.000	XM	−4.076	0.002	−7.187	0.000
IE	−4.902	0.000	−13.239	0.000					
IL	−4.264	0.001	−6.125	0.000	Panel	−26.403	0.000	−28.962	0.000

To rule out higher order of integration, Table 3 presents the results of ADF tests applied to the first difference of the credit-to-GDP ratio (Δy_t). With the exception of Spain and Greece, we are able to reject a unit root in Δy_t at the 10% significance level, and for most countries even at the 1% level. For Spain and Greece, we do reject a unit root if the lag length is set to 4, rather then selected by the AIC. For the Euro area (XM) as a whole, as well as for the full panel utilizing Choi's (2001) Z-test, we clearly reject a unit root

Table 4
Empirical results. This table reports correlations between credit gaps ($y_t - \tau_t$) and simple changes in the credit-to-GDP ratio ($y_t - y_{t-i}$). k is the optimal lag length (i) at which the correlation is maximized. $Cor(i)$ is the correlation between the credit gap and the i-quarter change. In addition to the optimal lag length, the correlations are reported also for 4, 8, 16, 24, 32, and 40 quarters. The final rows report the median and average across all 43 countries (excluding the Euro area).

	k	$Cor(k)$	$Cor(4)$	$Cor(8)$	$Cor(16)$	$Cor(24)$	$Cor(32)$	$Cor(40)$
AR	16	0.839	0.670	0.782	0.839	0.768	0.692	0.610
AT	17	0.941	0.672	0.844	0.937	0.869	0.735	0.645
AU	16	0.898	0.663	0.803	0.898	0.814	0.676	0.570
BE	12	0.811	0.630	0.775	0.796	0.695	0.558	0.473
BR	14	0.898	0.595	0.787	0.877	0.722	0.609	0.448
CA	15	0.922	0.679	0.839	0.921	0.856	0.771	0.670
CH	17	0.915	0.689	0.829	0.914	0.873	0.782	0.714
CL	17	0.864	0.615	0.788	0.864	0.803	0.635	0.413
CN	15	0.913	0.660	0.842	0.912	0.781	0.696	0.480
CO	13	0.936	0.626	0.825	0.890	0.660	0.408	0.272
CZ	13	0.901	0.693	0.852	0.893	0.804	0.579	0.300
DE	17	0.944	0.734	0.875	0.943	0.889	0.775	0.648
DK	18	0.942	0.716	0.842	0.939	0.903	0.793	0.626
ES	16	0.954	0.803	0.904	0.954	0.913	0.821	0.697
FI	17	0.931	0.637	0.811	0.930	0.892	0.774	0.638
FR	15	0.940	0.763	0.897	0.939	0.899	0.801	0.735
GB	17	0.895	0.677	0.814	0.895	0.855	0.742	0.602
GR	14	0.948	0.752	0.900	0.944	0.882	0.768	0.616
HK	17	0.959	0.729	0.880	0.955	0.912	0.904	0.877
HU	18	0.973	0.723	0.865	0.969	0.947	0.849	0.718
ID	17	0.847	0.628	0.768	0.847	0.805	0.748	0.660
IE	15	0.927	0.735	0.875	0.927	0.867	0.771	0.636
IL	15	0.926	0.742	0.884	0.924	0.858	0.731	0.649
IN	18	0.945	0.707	0.848	0.942	0.907	0.815	0.672
IT	15	0.913	0.719	0.843	0.912	0.861	0.745	0.597
JP	13	0.899	0.786	0.875	0.889	0.825	0.728	0.606
KR	15	0.914	0.673	0.834	0.913	0.849	0.690	0.465
LU	28	0.863	0.690	0.799	0.824	0.831	0.837	0.669
MX	15	0.932	0.719	0.854	0.928	0.839	0.692	0.553
MY	15	0.885	0.655	0.805	0.884	0.840	0.769	0.618
NL	14	0.948	0.740	0.884	0.945	0.895	0.812	0.695
NO	14	0.884	0.626	0.794	0.880	0.827	0.722	0.553
NZ	15	0.870	0.654	0.792	0.870	0.803	0.688	0.575
PL	14	0.927	0.715	0.866	0.921	0.851	0.800	0.686
PT	16	0.955	0.766	0.883	0.955	0.915	0.821	0.722
RU	12	0.940	0.676	0.855	0.877	0.570	0.459	0.521
SA	10	0.940	0.776	0.925	0.822	0.719	0.818	0.865
SE	17	0.893	0.643	0.798	0.891	0.847	0.700	0.554
SG	15	0.918	0.668	0.827	0.916	0.861	0.785	0.618
TH	17	0.925	0.710	0.831	0.924	0.893	0.800	0.666
TR	12	0.930	0.692	0.851	0.926	0.839	0.679	0.539
US	18	0.958	0.695	0.845	0.955	0.924	0.807	0.649
ZA	15	0.877	0.637	0.796	0.874	0.736	0.569	0.503
XM	12	0.958	0.713	0.907	0.929	0.845	0.772	0.701
Median	15	0.925	0.690	0.842	0.914	0.851	0.748	0.618
Average	15.56	0.915	0.692	0.839	0.906	0.835	0.729	0.605

in Δy_t. Taken together, the results in Tables 2 and 3 suggest that the credit-to-GDP ratio is first-order integrated, or $I(1)$, such that these variables are subject to the mechanical correlations between a gap measure based on HP filter trend endpoints and changes, as documented in Sections 2 and 3 above.

In Table 4, we report the correlation coefficients between the credit gaps and k-quarter changes in the credit-to-GDP ratio ($\Delta_k y_t = y_t - y_{t-k}$) for each country. The first column reports the lag k at which the correlation is maximized, while the second column shows the maximum correlation. This correlation is remarkably high across all countries, ranging from 0.81 (Belgium) to 0.97 (Hungary). On average across all 43 countries (excluding the Euro area), the correlation is 0.92. The lag at which the correlation is highest is in general close to 16, with a median of 15 and average of 15.6. Table 4 also reports the correlation for other selected values of k, showing in general a hump-shaped pattern very similar to the analytical results in Fig. 3 and the simulation results in Fig. 4.

Table 5 presents the correlation-maximizing lags and the corresponding maximum correlations when the HP filter smoothing parameter λ is set to either 1600 or 25,000, instead of 400,000, in the calculation of the credit gap. Consistent with the analytical and simulation results above, lowering the smoothing parameter simply results in the credit gap measure being correlated with shorter changes in the credit ratio. The median correlation maximizing lag is $k = 4$ when $\lambda = 1600$, and $k = 8$ when $\lambda = 25{,}000$.

Table 5
Different smoothing parameters. This table reports correlations between credit gaps ($y_t - \tau_t$) and simple changes in the credit-to-GDP ratio ($y_t - y_{t-i}$), for different values of the smoothing parameter, λ, used in the HP filter. k is the optimal lag length (i) at which the correlation between the credit gap and the simple change is maximized. $Cor(k)$ is the correlation between the credit gap and the k-quarter change. The final rows report the median and average across all 43 countries (excluding the Euro area).

	$\lambda = 1600$		$\lambda = 25{,}000$		$\lambda = 400{,}000$	
	k	$Cor(k)$	k	$Cor(k)$	k	$Cor(k)$
AR	4	0.892	7	0.843	16	0.839
AT	5	0.826	7	0.903	17	0.941
AU	4	0.837	9	0.909	16	0.898
BE	4	0.867	7	0.832	12	0.811
BR	4	0.793	7	0.735	14	0.898
CA	4	0.860	9	0.879	15	0.922
CH	4	0.850	9	0.869	17	0.915
CL	4	0.880	8	0.880	17	0.864
CN	4	0.845	8	0.844	15	0.913
CO	4	0.817	8	0.779	13	0.936
CZ	3	0.641	6	0.824	13	0.901
DE	3	0.778	7	0.846	17	0.944
DK	3	0.737	8	0.879	18	0.942
ES	3	0.645	5	0.878	16	0.954
FI	4	0.842	9	0.898	17	0.931
FR	3	0.866	8	0.865	15	0.940
GB	4	0.731	7	0.864	17	0.895
GR	3	0.695	6	0.804	14	0.948
HK	4	0.811	6	0.851	17	0.959
HU	3	0.718	7	0.892	18	0.973
ID	4	0.886	7	0.843	17	0.847
IE	3	0.803	7	0.853	15	0.927
IL	3	0.760	5	0.737	15	0.926
IN	3	0.724	7	0.857	18	0.945
IT	3	0.720	7	0.833	15	0.913
JP	3	0.703	6	0.774	13	0.899
KR	4	0.880	9	0.933	15	0.914
LU	4	0.903	8	0.883	28	0.863
MX	3	0.826	9	0.940	15	0.932
MY	4	0.838	8	0.856	15	0.885
NL	3	0.853	9	0.956	14	0.948
NO	4	0.890	8	0.879	14	0.884
NZ	4	0.798	8	0.864	15	0.870
PL	4	0.880	9	0.942	14	0.927
PT	3	0.734	6	0.870	16	0.955
RU	5	0.942	10	0.927	12	0.940
SA	4	0.951	9	0.953	10	0.940
SE	4	0.814	8	0.855	17	0.893
SG	4	0.862	9	0.919	15	0.918
TH	3	0.775	8	0.871	17	0.925
TR	4	0.828	9	0.790	12	0.930
US	3	0.786	7	0.921	18	0.958
ZA	4	0.883	9	0.905	15	0.877
XM	4	0.862	6	0.944	12	0.958
Median	4	0.826	8	0.869	15	0.925
Average	3.65	0.813	7.67	0.866	15.56	0.915

On average, the maximum correlations are high: 0.83 for λ = 1600 and 0.88 for λ = 25,000. These values are very similar to the analytical and simulation results presented in Figs. 3 and 4.

While the patterns of correlations between the credit gap and changes in the credit-to-GDP ratio are similar across countries, the historical developments of the credit ratio itself differ widely. Fig. 5 visually illustrates how the high correlations arise for three selected countries with very different patterns of the credit ratio: Italy, Japan, and Finland. The left panels of the figure show the credit-to-GDP ratio (black line) and the one-sided HP filter trend estimates (blue line), similar to Panel D of Fig. 2 for the UK. The right panels show the resulting credit gap (blue line) and the simple 16-quarter change in the credit-to-GDP ratio (red line). Similar to the case of the UK, the one-sided trend estimates are clearly lagging the original credit-to-GDP ratio for each country. This is particularly visible for Italy and Japan, which both experience prolonged periods of growth and decline in the credit ratio. The right panels show, similar to Fig. 1, that the credit gaps and naive changes are not only highly correlated, but experience peaks and troughs simultaneously. This continues to be the case during more extreme cyclical movements, such as in Finland during the early 1990's. The credit cycles identified by the simple 16-quarter changes are thus nearly identical to the credit gaps estimated by a one-sided HP filter.

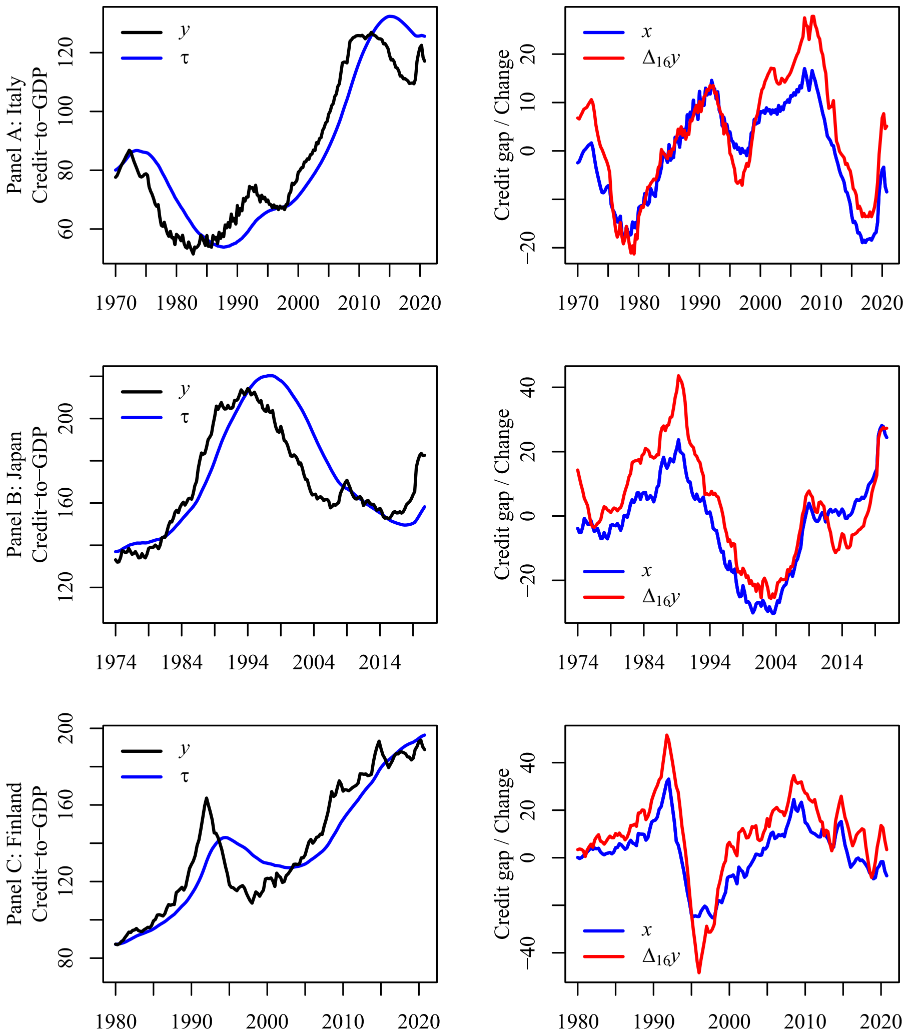

Fig. 5. Other countries. This figure presents the empirical results for Italy, Japan, and Finland. The left panels show the credit-to-GDP ratios (y_t, black line) and the one-sided HP filter trends (τ_t, blue line). The right panels show the resulting credit gaps ($x_t = y_t - \tau_t$, blue line) and the simple 16-quarter changes in the credit-to-GDP ratio ($\Delta_{16} y_t = y_t - y_{t-16}$, red line). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5. Predicting banking crises

In this section, we compare the credit gap to the 16-quarter change in the credit-to-GDP ratio in terms of their ability to predict banking crises. Drehmann and Juselius (2014) justify the use of the credit gap as an early warning indicator, by demonstrating its superior predictive power for banking crises. Drehmann and Juselius (2014) treat the prediction of crisis episodes as a binary classification problem, by evaluating whether the level of the indicator predicts the start of a crisis within the next h quarters, applying the Receiver Operating Characteristic (ROC) curve. The ROC curve plots the true positive rate against the false positive rate, for all possible threshold levels of the indicator. The *Area Under the Curve* (AUC) is a convenient summary statistic of the predictive power of an indicator: A fully informative indicator (implying no false positives) has an AUC of 1, while a fully inaccurate indicator (implying no true positives) has an AUC of 0. An uninformative indicator (e.g., the flip of a coin) is expected to have an AUC of 0.5.[8]

Using a sample of 19 banking crises, Drehmann and Juselius (2014) obtain the AUCs of various potential early warning indicators and find that the credit gap performs best (i.e., has the highest AUC) at prediction horizons h exceeding 6 quarters. We use the same sample of crises and the same ROC-AUC methodology to compare the credit gap to the 16-quarter change in the credit-to-GDP

[8] See Robin et al. (2011) for details on the ROC methodology and on the “pROC” package in R (R Core Team, 2022). Recent applications in economics include Berge and Jordà (2011) and Costa et al. (2019).

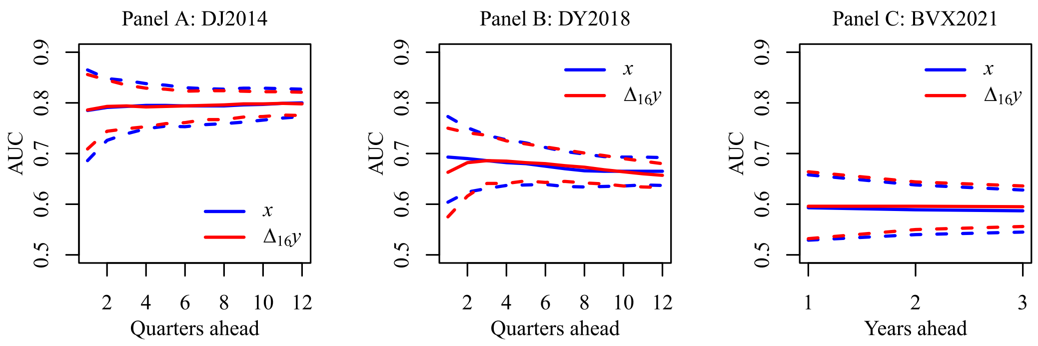

Fig. 6. Predicting banking crises. This figure presents the area under the ROC curve (AUC) for the credit gap ($x_t = y_t - \tau_t$, blue line) and the simple 16-quarter changes in the credit-to-GDP ratio ($\Delta_{16}y_t = y_t - y_{t-16}$, red line). In Panel A, the AUCs are obtained with quarterly observations of both indicators, predicting banking crises from one up to 12 quarters ahead, using a sample of 19 banking crises (Drehmann and Juselius, 2014). In Panel B, the AUCs are obtained with quarterly observations using a sample of 59 banking crises (Drehmann and Yetman, 2021). In Panel C, the AUCs are obtained with annual (Q4) observations of both indicators, predicting banking crises from one up to 3 years ahead, using a broader sample of 95 banking crises (Baron et al., 2021). The dashed lines represent bootstrapped 95% confidence intervals. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

ratio.[9] The blue line in Panel A of Fig. 6 reports the AUC for the credit gap at horizons of one up to twelve quarters. The red line, showing the AUC for the 16-quarter change in the credit-to-GDP ratio almost fully overlaps with the credit gap's AUC. Based on the bootstrapped 95% confidence bounds, the differences are clearly not significant. Thus, in line with our earlier results that the credit gap and 16-quarter change are highly similar, we now also document that these measures are nearly equivalent when it comes to predicting banking crises.

In response to Hamilton's (2018) critique on the use of the HP filter and recommendation to apply local projections, Drehmann and Yetman (2021) consider an extended sample and show that linear projections do not outperform the credit gap based on HP filter in term of predicting crises. In panel B of Fig. 6, we report the AUC for the credit gap (blue line) and for the 16-quarter change (red line), using a sample of 59 crises. Similar to Panel A, there is no significant difference between the two measures in terms of predicting banking crises.

In a recent article, Baron et al. (2021) argue that prior literature on banking distress focuses primarily on salient episodes of distress coinciding with banking panics, while banking crises have severe economic consequences even in the absence of a simultaneous panic. By defining banking crises as declines in bank equity of at least 30%, Baron et al. (2021) build a novel database of banking crises that includes several "quiet" episodes that are not accounted for in earlier studies.

Using this broader sample of 95 banking crises, we repeat our prediction exercise comparing the credit gap to the 16-quarter change in the credit-to-GDP ratio.[10] As the crisis dates are documented at annual frequency by Baron et al. (2021), we only use the end-of-year (Q4) observations of the credit gap and 16-quarter change, and evaluate predictive power from one up to three years ahead. Panel C of Fig. 6 reports the AUC for the credit gap (blue line) and the 16-quarter change in the credit-to-GDP ratio (red line). The AUCs of both indicators are around 0.6, which is considerably lower than in Panel A. Both the credit gap and the 16-quarter change thus clearly perform worse as an early warning indicator, when applied to a broader sample of banking crises. As before, the credit gap and 16-quarter change behave in a highly similar manner, with the difference in predictive power not being statistically significant.

Finally, we use the sample by Baron et al. (2021) to evaluate the predictability of banking crises in a regression context. Following Candelon et al. (2014), we apply the following four dynamic probit regressions, introduced by Kauppi and Saikkonen (2008):

$$\begin{array}{llcllcl} \text{Model 1}: & Pr(d_{i,t}=1) & = & F(\pi_{i,t}) & = & F(\alpha+\beta x_{i,t-1}) \\ \text{Model 2}: & Pr(d_{i,t}=1) & = & F(\pi_{i,t}) & = & F(\alpha+\beta x_{i,t-1}+\rho d_{i,t-1}) \\ \text{Model 3}: & Pr(d_{i,t}=1) & = & F(\pi_{i,t}) & = & F(\alpha+\beta x_{i,t-1}+\gamma \pi_{i,t-1}) \\ \text{Model 4}: & Pr(d_{i,t}=1) & = & F(\pi_{i,t}) & = & F(\alpha+\beta x_{i,t-1}+\rho d_{i,t-1}+\gamma \pi_{i,t-1},) \end{array} \tag{8}$$

in which the probability of a crisis in country i at time t ($d_{i,t}=1$) is modeled as a function of a lagged predictor $x_{i,t-1}$, supplemented with a lagged crisis indicator $d_{i,t-1}$ and/or an autoregressive term $\pi_{i,t-1}$. We apply these four specifications to the set of crises identified by Baron et al. (2021), using both the credit gap and 16-quarter change as predictors.[11]

[9] The sample of 19 banking crises comprises the 'balanced sample' listed in Table A.1 of Drehmann and Juselius (2014). Using their 'unbalanced sample' of 34 crises, we obtain qualitatively similar results.

[10] Our initial sample consists of all crises listed in Table 6 of Baron et al. (2021) for which 'bank equity crisis' = 1. After matching this sample to the BIS data (See Section 4) and dropping crises that are preceded within the same country by another crisis during the previous two years (following Laeven and Valencia, 2013), we end up with a final sample of 95 crises.

[11] We estimate the models using the dynamic panel probit estimator by Candelon et al. (2014), which is implemented in the "EWS" package in R (Hasse and Lajaunie, 2021; R Core Team, 2022). Our sample differs in two ways from the sample used for the ROC analysis presented in Fig. 6 (Panel C). First, given the

Table 6
Dynamic probit regressions. This table reports the results from regressing a dummy variable $d_{i,t}$, indicating whether country i in year t is experiencing a banking crisis, on a lagged predictor $x_{i,t-1}$, a lagged crisis dummy $d_{i,t-1}$ and/or an autoregressive term $\pi_{i,t-1}$. The four model specifications, following Kauppi and Saikkonen (2008) and Candelon et al. (2014) are listed in Eq. (8). The predictor $x_{i,t-1}$ is either the previous year (quarter 4) credit gap ($y_t - \tau_t$) or a simple 16-quarter change in the credit-to-GDP ratio ($y_t - y_{t-16}$). The crises episodes are from the database by Baron et al. (2021). The balanced sample includes 28 countries with 36 annual observations each (1984–2019). Z-statistics are reported in parentheses.

x_{t-1}	Model 1		Model 2		Model 3		Model 4	
	Gap	Change	Gap	Change	Gap	Change	Gap	Change
Intercept	−2.06	−2.76	−3.40	−3.71	−0.56	−0.73	−3.98	−4.43
	(−2.26)	(−2.15)	(−4.89)	(−4.91)	(−3.21)	(−4.19)	(−4.35)	(−4.32)
x_{t-1}	0.06	0.05	0.05	0.03	0.04	0.03	0.06	0.04
	(4.78)	(5.99)	(4.57)	(4.16)	(7.77)	(9.33)	(4.03)	(3.81)
y_{t-1}			3.59	3.52			4.15	4.13
			(19.77)	(19.85)			(16.36)	(15.89)
π_{t-1}					−0.74	−0.60	−0.23	−0.10
					(−2.42)	(−2.32)	(−0.17)	(−0.08)
Observations	1008	1008	1008	1008	1008	1008	1008	1008
Pseudo-R^2	0.090	0.112	0.383	0.380	0.112	0.128	0.390	0.392
AIC	708.6	691.4	470.4	473.1	692.4	679.0	465.3	463.9

The results, reported in Table 6, demonstrate again near equivalence between the credit gap and the 16-quarter change in terms of predicting banking crises one year forward. Based on the reported AIC and Pseudo-R^2, the 16-quarter change performs marginally better in Models 1, 3 and 4, while the credit gap performs marginally better in Model 2. For both predictors, the full dynamic autoregressive specification (Model 4) performs best. Utilizing three sets of crises and two distinct forecasting approaches, the results in this section demonstrate that there is no meaningful difference in the predictive power of the credit gap and the 16-quarter change in terms of predicting systemic risk over short to intermediate horizons.

6. Conclusion

We document that the credit gap or 'Basel gap' is nearly equivalent to a simple 16-quarter change in the credit-to-GDP ratio. This similarity is the result of the recursive trend-estimation underlying the credit gap, using the one-sided HP filter, which results in a trend component that is mechanically lagging the original credit-to-GDP ratio. We illustrate this finding using data from the UK and document similar results using data from other countries. For each of the 44 countries we investigate, the correlation between the credit gap and the 16-quarter change in the credit-to-GDP ratio is between 0.80 and 0.97. We also conduct a Monte Carlo exercise and find similar results when applying one-sided HP filtration to simulated time series. When evaluating the performance of the credit gap and the 16-quarter change as early warning indicators, we find that their performance in terms of predicting banking crises are nearly identical. This holds both within samples of crises used earlier to evaluate the credit gap, as well as in a larger sample of more broadly defined banking crises.

Whether the credit gap is the optimal indicator for identifying credit cycles and setting countercyclical regulatory capital buffers remains an open question that we do not aim to answer in this paper. Several studies have warned explicitly against the use of the Basel credit gap as an early warning indicator (e.g. Edge and Meisenzahl, 2011; Repullo and Saurina Salas, 2011; Alessi and Detken, 2018; Geršl and Jašová, 2018; Afanasyeva, 2020), while Tölö et al. (2018) recommend to consider other early warning indicators (including stock market volatility, credit spreads and real estate prices) in addition to the credit gap. Jokipii et al. (2021) acknowledge its methodological concerns, but consider the credit gap nevertheless a reliable measure of excess credit in Switzerland. Rather than taking a stance on whether or not the Basel credit gap is an appropriate measure of systemic risk, our objective is to demonstrate its equivalence to a naive 16-quarter change. This implies that the estimation procedure underlying the credit gap is unnecessarily complicated and obscure. There is ultimately no need to use complicated methods when simple changes suffice. Compared to applying a one-sided HP filter, taking a simple change is undoubtedly easier to communicate, both to policy makers and to the broader public. Although the credit gap has the appealing and intuitive interpretation of indicating a deviation from the long-term trend, this interpretation is potentially highly misleading when the 'trend' is effectively the lag of the credit-to-GDP ratio. We therefore recommend estimating the credit gap more transparently by a simple 16-quarter change in the credit-to-GDP ratio.

Of course, it is possible that a lag length different than 16 quarters could lead to better performance in terms of predicting systemic risk. For example, Hamilton (2018, 2021) proposes a two-year difference as a robust approach to identify cycles from many monthly economic time series. Adjusting the lag-structure to improve the credit gap as an early warning indicator is a possible avenue for future research.

dynamic autoregressive specification of the model, we do not need to adopt the procedure by Laeven and Valencia (2013) to exclude crises that are preceded within the same country by another crisis during the previous two years. Second, since the data needs to be in a balanced panel format, we choose the number of countries N and time periods T such that $N \times T$ is maximized. We end up with a sample of $N = 28$ countries, for which we use $T = 36$ annual observations of data (1984–2019), yielding a total of 1008 observations.

Our results have broader implications for the application of the one-sided HP filter. We find in general that the cyclical component of an $I(1)$ process, estimated by a one-sided HP filter, is highly correlated with the k-period change in the process. This result holds for different values of the smoothing parameter λ. When the smoothing parameter is decreased, the deviation from trend approximates a shorter change in the credit-to-GDP ratio. Calibrating the smoothing parameter is thus effectively equivalent to calibrating the lag length k over which changes are calculated. We thus conclude that the one-sided HP filter does not succeed in identifying cycles from a process that has order of integration less than two.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Supplementary analytical results

Cornea-Madeira (2017, Theorem 1, p. 315) finds analytical solutions of the HP filter that are valid for an entire sample, including the endpoints. Specifically, the ith observation of the trend of a time series of length T is specified as: $\tau_i = \sum_{t=1}^{T} p_{i,t} y_t$, where the weights $p_{i,t}$ are a function of the smoothing parameter λ, t, i and T, but do not depend on the distribution of y_t (See Corollary 1, Cornea-Madeira, 2017). As we are solely interested in the last observation of the trend, we can simplify notation to

$$\tau_T = \sum_{t=1}^{T} p_t y_t,$$

as in Eq. (2).

Table A.1 tabulates selected weights p_t, calculated using the expressions provided by Cornea-Madeira (2017), for different values of T and λ. The table shows that the endpoint of the trend is a weighted average of past observations, with most weight given to the most recent observations. A lower smoothing parameter λ implies relatively higher weights for the most recent observations. It is also clear that the weights of the observations towards the end of the sample do not strongly depend on the sample size T.

Given the weights of each observation, we can derive the correlation between y_T in deviation from trend, and y_T in deviation from its k-order lag, for any $I(1)$ time-series process y_t, such that $\Delta y_t = \xi_t$ is a stationary process. For example, when y_t is a random walk: $\xi_t \sim i.i.d.(0, \sigma^2)$, it follows that:

$$\begin{aligned}
var\left(x_T\right) &= var\left(\sum_{t=1}^{T}\left(1-\varphi_t\right)\xi_t\right) \\
&= \sum_{t=1}^{T}\left(1-\varphi_t\right)^2\sigma^2 \\
var\left(\Delta_k y_T\right) &= var\left(\sum_{t=T-k+1}^{T}\xi_t\right) \\
&= k\sigma^2 \\
cov\left(x_T, \Delta_k y_T\right) &= cov\left(\sum_{t=1}^{T}\left(1-\varphi_t\right)\xi_t, \sum_{t=T-k+1}^{T}\xi_t\right) \\
&= cov\left(\sum_{t=T-k+1}^{T}\left(1-\varphi_t\right)\xi_t, \sum_{t=T-k+1}^{T}\xi_t\right) \\
&= \sum_{t=T-k+1}^{T}\left(1-\varphi_t\right)\sigma^2 \\
cor\left(x_T, \Delta_k y_T\right) &= \frac{\sum_{t=T-k+1}^{T}\left(1-\varphi_t\right)}{\sqrt{k\sum_{t=1}^{T}\left(1-\varphi_t\right)^2}},
\end{aligned}$$

where $\varphi_t = \sum_{j=t}^{T} p_j$. In general, for any $I(1)$ process $\mathbf{y}$ of length T, such that $\mathbf{\Delta y} = \xi = \begin{bmatrix}\xi_1 \\ \vdots \\ \xi_T\end{bmatrix} \sim (\mathbf{0}, \mathbf{\Sigma})$; we can define $x_T = (\mathbf{1}-\varphi)'\xi$, where $\varphi = \begin{bmatrix}\varphi_1 \\ \vdots \\ \varphi_T\end{bmatrix}$ and $\Delta_k y_T = \delta^{(\mathbf{k})\prime}\xi$, where $\delta^{(\mathbf{k})} = \begin{bmatrix}\delta_1^{(k)} \\ \vdots \\ \delta_{T-k}^{(k)} \\ \delta_{T-k+1}^{(k)} \\ \vdots \\ \delta_T^{(k)}\end{bmatrix} = \begin{bmatrix}0 \\ \vdots \\ 0 \\ 1 \\ \vdots \\ 1\end{bmatrix}$. The second-order moments of x_T and $\Delta_k y_T$ are:

$$\begin{aligned}
var\left(x_T\right) &= var\left((\mathbf{1}-\varphi)'\xi\right) \\
&= (\mathbf{1}-\varphi)'\mathbf{\Sigma}(\mathbf{1}-\varphi) \\
var\left(\Delta_k y_T\right) &= var\left(\delta^{(\mathbf{k})\prime}\xi\right) \\
&= \delta^{(\mathbf{k})\prime}\mathbf{\Sigma}\delta^{(\mathbf{k})} \\
cov\left(x_T, \Delta_k y_T\right) &= cov\left((\mathbf{1}-\varphi)'\xi, \delta^{(\mathbf{k})\prime}\xi\right) \\
&= (\mathbf{1}-\varphi)'\mathbf{\Sigma}\delta^{(\mathbf{k})}
\end{aligned}$$

Table A.2 reports the correlations between x_T and $\Delta_k y_T$ for $k = 1, \ldots, 20$, for different specification of y_t and different values of λ and T. In the first three columns, y_t is a random walk and $T = 200$, as in Fig. 3. The next three columns show that the correlations are

Table A.1
Weights. This table reports the weights p_t in $\tau_T = \sum_{t=1}^{T} p_t y_t$ (Eq. (2)), calculated using the expressions provided by Cornea-Madeira (2017), for selected t and for different values of the smoothing parameter λ and sample size T.

	$\lambda = 400{,}000$			$\lambda = 25{,}000$			$\lambda = 1{,}600$		
t	$T = 100$	$T = 200$	$T = 1{,}000$	$T = 100$	$T = 200$	$T = 1{,}000$	$T = 100$	$T = 200$	$T = 1{,}000$
T	0.0554	0.0547	0.0547	0.1064	0.1064	0.1064	0.2006	0.2006	0.2006
$T-1$	0.0539	0.0532	0.0531	0.1004	0.1004	0.1004	0.1782	0.1782	0.1782
$T-2$	0.0523	0.0516	0.0516	0.0945	0.0945	0.0945	0.1564	0.1564	0.1564
$T-3$	0.0508	0.0501	0.0501	0.0886	0.0886	0.0886	0.1354	0.1354	0.1354
$T-4$	0.0493	0.0486	0.0486	0.0828	0.0828	0.0828	0.1156	0.1156	0.1156
$T-5$	0.0478	0.0470	0.0470	0.0772	0.0772	0.0772	0.0972	0.0972	0.0972
$T-6$	0.0463	0.0455	0.0455	0.0717	0.0716	0.0716	0.0803	0.0803	0.0803
$T-7$	0.0448	0.0441	0.0440	0.0663	0.0663	0.0663	0.0650	0.0650	0.0650
$T-8$	0.0433	0.0426	0.0426	0.0611	0.0611	0.0611	0.0513	0.0513	0.0513
$T-9$	0.0418	0.0411	0.0411	0.0561	0.0561	0.0561	0.0393	0.0393	0.0393
$T-10$	0.0404	0.0397	0.0397	0.0513	0.0513	0.0513	0.0287	0.0287	0.0287
$T-20$	0.0270	0.0264	0.0264	0.0149	0.0149	0.0149	−0.0132	−0.0132	−0.0132
$T-50$	0.0022	0.0022	0.0022	−0.0061	−0.0060	−0.0060	0.0006	0.0006	0.0006
$T-99$	−0.0085	−0.0032	−0.0032	0.0011	0.0003	0.0003	0.0000	0.0000	0.0000

Table A.2
Correlations. This table reports $cor\left(x_T, \Delta_k y_T\right)$, the correlation between the endpoint of a time-series y_T in deviation from trend and in deviation from its k-order lag, for $k = 1, \ldots, 20$. The correlation is derived using the weights calculated following Cornea-Madeira (2017), for different values of the smoothing parameter λ and sample size T, see Table A.1. The first 6 columns consider a random walk process ($\Delta y_t = \xi_t \sim i.i.d.(0, \sigma^2)$). In the last three columns, y_t is a random walk with time-varying variance: $var(\xi_t) = 1 + \cos\left(\frac{t}{2\pi}\right)$.

	Random walk $T = 200$			Random walk $T = 1{,}000$			Time-varying variance $T = 200$		
λ	400,000	25,000	1,600	400,000	25,000	1,600	400,000	25,000	1,600
$k = 1$	0.3261	0.4485	0.5989	0.3261	0.4485	0.5989	0.3602	0.4761	0.6389
2	0.4483	0.5987	0.7525	0.4482	0.5987	0.7525	0.4982	0.6393	0.8069
3	0.5334	0.6913	0.8155	0.5334	0.6913	0.8155	0.5954	0.741	0.8767
4	0.5983	0.7518	0.8297	0.5982	0.7518	0.8297	0.6693	0.8074	0.8929
5	0.6496	0.7907	0.8137	0.6495	0.7907	0.8137	0.7270	0.8497	0.8761
6	0.6909	0.8141	0.7785	0.6908	0.8141	0.7785	0.7723	0.8744	0.8390
7	0.7243	0.8255	0.7311	0.7242	0.8255	0.7311	0.8077	0.8859	0.7904
8	0.7514	0.8276	0.6763	0.7513	0.8276	0.6763	0.8350	0.8877	0.7363
9	0.7731	0.8222	0.6176	0.7730	0.8222	0.6176	0.8555	0.8823	0.6812
10	0.7903	0.8110	0.5577	0.7902	0.8110	0.5577	0.8704	0.8718	0.6283
11	0.8037	0.7950	0.4983	0.8036	0.7950	0.4983	0.8808	0.8582	0.5796
12	0.8136	0.7752	0.4409	0.8136	0.7752	0.4409	0.8875	0.8429	0.5366
13	0.8207	0.7524	0.3863	0.8206	0.7524	0.3863	0.8914	0.8271	0.4998
14	0.8250	0.7273	0.3352	0.8250	0.7273	0.3352	0.8930	0.8118	0.4695
15	0.8271	0.7003	0.2880	0.8270	0.7003	0.2880	0.8932	0.7977	0.4454
16	0.8271	0.6720	0.2448	0.8271	0.6720	0.2448	0.8923	0.7855	0.4269
17	0.8253	0.6429	0.2058	0.8252	0.6429	0.2058	0.8910	0.7754	0.4135
18	0.8218	0.6131	0.1710	0.8217	0.6131	0.1710	0.8895	0.7676	0.4043
19	0.8168	0.5830	0.1401	0.8168	0.5830	0.1401	0.8882	0.7621	0.3984
20	0.8106	0.5529	0.1129	0.8105	0.5529	0.1129	0.8872	0.7586	0.3951

nearly identical when the sample size is increased to $T = 1{,}000$. This result is expected, since the weights as reported in Table A.1 are not sensitive to T. The final columns of Table A.2 show the correlations for a random walk process y_t with time-varying variance: $var(\xi_t) = 1 + \cos\left(\frac{t}{2\pi}\right)$, generating cycles of approximately 20 periods (7 years with quarterly data) in the level of volatility. These correlations peak at the same lag k as for the random walks. Introducing time-varying volatility increases the correlations, which get closer to the empirically observed correlations (Table 4).

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