Mind the Basel Gap *

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Abstract

The Basel gap, the difference between a country's credit-to-GDP ratio and its estimated long-term trend, is used as a basis for setting the countercyclical regulatory capital buffers under the Basel III regulatory framework. Using international data from the BIS as well as simulations, we show that the Basel gap, estimated by a one-sided HP filter, is nearly equivalent to a naive 16-quarter change in the credit-to-GDP ratio. We demonstrate that the near-equivalence between deviations from trend and simple changes occurs when the one-sided HP filter is applied to an $I(1)$ process.

Keywords: One-sided Hodrick-Prescott filter, Basel gap, Credit, Banking crises.
JEL classification: C22, E52, G28

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1 Introduction

The Basel gap, an early warning signal of financial crises defined as a country's credit-to-GDP ratio in deviation of its long-term trend, is the primary measure considered by policy makers when determining countercyclical regulatory capital buffers under the Basel III framework.[1] Due to its role in setting banking capital requirements, the methodology underlying the Basel gap has important real implications. As with any such actual-minus-trend gap measure, a crucial step in constructing the Basel gap is defining the long-term trend of the credit-to-GDP ratio. The Basel gap is calculated following the methodology by Drehman et al. (2010), who apply a Hodrick-Prescott (1981, 1997) filter recursively to obtain the trend.

We document in this paper that the implementation of the one-sided HP filter causes the Basel 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 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 consist 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. De Jong and Sakarya (2016), as well as Hamilton (2018), also note that the behavior at the endpoints of the HP filtered trend behave considerably different from trend estimates in the middle of the sample. Corneia-Madeira (2018) obtains analytical expressions for the endpoints of the trend. Applying the results of Corneia-Madeira (2018), we find that deviations from these trend endpoints approximate time-series changes of the original series when applied to an $I(1)$ process. King and Rebelo (1993) and Cogley and Nason (1995) find that the Hodrick-Prescott is not optimal when applied to a time series integrated of order less than two. We show indeed that when estimating the trend of a time-series process that is second-order integrated, or $I(2)$, the near-equivalence between estimated deviations from trend and simple changes in general does not apply. We

[1] For example, the European Systemic Risk Board recommends that the benchmark buffer is set at the maximum level of 2.5% when the Basel 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).

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 Basel gap (deviation from trend) and the change in the credit-to-GDP ratio is illustrated below in Figure 1, using 184 quarterly observations of the credit-to-GDP ratio in the United Kingdom from 1973 to 2018.[2] The Basel 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 change in the credit-to-GDP ratio. In addition to a high correlation of 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 44 countries, we find a striking similarity between the Basel gap and a naive 16-quarter change in the credit-to-GDP ratio, with an average correlation of 92%. In addition to our analytical an 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 Basel gap performs as good (or bad) as a naive 16-quarter change in the credit-to-GDP ratio. In general, time-series changes and deviations from trend are not equivalent. It is well possible for a variable to be below (above) trend, even if the variable recently increased (decreased). The Basel gap however seems to identify changes, rather than actual deviations from trend.

[Figure 1 here]

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. Within the context of identifying credit cycles, both Repullo and Saurina Salas (2011) and Alessi and Detken (2018) point out that

[2] The data for the credit-to-GDP ratio is from BIS and available at `https://www.bis.org/statistics/c_gaps.htm`.

Drehman 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 Basel gap to move slowly, in particular following periods of negative GDP growth. When the objective is identification of business cycle (approximately 2-8 years in duration) fluctuations, it is common practice with quarterly data to apply the HP filter with a smoothing parameter (λ) of 1,600. The calibration by Drehman et al. (2010) is motivated by the observation that credit cycles are much 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.

This paper proceeds as follows: in Section 2 we describe the methodology underlying the Basel gap and provide analytical and simulation results documenting the similarity between the estimated deviation from trend and simple time-series changes. Section 3 provides empirical results for the 43 countries in our sample. Section 4 concludes.

2 Analytical background

2.1 Basel gap

The Basel 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:

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

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 Basel gap is estimated with a smoothing parameter of $\lambda = 400{,}000$ (Drehman et al.,2010).

Figure 2 illustrates the estimation of the one-sided HP filter using the UK credit-to-GDP data as an example. The black line in Panel A shows the credit-to-GDP ratio from 1973 to 2018. 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.

[Figure 2 here]

The red line, however, is not the trend used for the calculation of the Basel gap. Rather, the trend required for obtaining the Basel gap is estimated by the so-called one-sided HP filter, which is implemented recursively. To illustrate, the red line in Panel B of Figure 2 shows the trend component estimated using only data available up to 1988, with the blue dot marking the endpoint. Panel C displays the endpoints of trends estimated using data up to 1988, 1998, 2008, and 2018. The thin red lines in Panel D show 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 Basel 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.

2.2 Analytical expressions

Several studies (e.g. Mise et al., 2005; De Jong and Sakarya, 2016; Hamilton, 2016) 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 Cornea-Madeira (2017) to demonstrate that the last observation of an $I(1)$ time-series in deviation of its estimated trend is highly correlated to the last observation of the time-series in deviation of its own higher-order 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:

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

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

$$\begin{aligned}
x_T &= y_T - \tau_T \\
&= \textstyle\sum_{t=1}^{T} \xi_t - \sum_{t=1}^{T} \varphi_t \xi_t \\
&= \textstyle\sum_{t=1}^{T} (1 - \varphi_t)\, \xi_t.
\end{aligned} \tag{5}$$

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

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

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

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 show that:

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

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

[Figure 3 here]

The blue dots in the figure are based on UK data, indicating the correlation coefficients between the Basel gap and changes in the credit-to-GDP ratio, for different lag lengths over which the change is computed.[4] The theoretical correlations in red and the empirical correlations in blue show a very similar pattern, with the correlation between the Basel gap and an k-quarter change in the credit-to-GDP ratio being maximized at 0.9 with k=16. In general, the empirical correlations are higher than the theoretical correlations. As we show in Appendix A, 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 T, as demonstrated in Appendix A.

[4]Note that the red dots of Figure 3 shows the theoretical correlation for a fixed sample size of T=200. The empirical plot is based on a sample of 182 observations, where the endpoints of the trends and the time-series differences are obtained at every observation $t = 1, \ldots, 182$.

The theoretical correlations between changes and trend endpoints $cor(x_T, \Delta_s y_T)$ can be derived only when ξ_t (the first-order change in y_t) is stationary. When y_t is of order of integration of $I(2)$ or higher, ξ_t is no longer stationary meaning that its population covariance with the trend endpoints is 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 $I(2)$ process.

2.3 The role of λ

Repullo and Saurina Salas (2011) and Alessi and Detken (2018) criticize the Basel 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 λ=1,600 (Hodrick and Prescott, 1981). Drehman et al. (2010) find that a smoothing parameter of λ=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 Basel gap moves too slowly, in particular following periods of negative GDP growth.

Our observation that the one-sided trend mechanically lags the credit-to-GDP ratio is a distinct concern from 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 parameter, the gap approximates a shorter difference in the credit-to-GDP ratio. We show in Panels B and C of Figure 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 λ=1,600 or λ=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 λ=1,600 and at k=8 for λ=25,000.

The blue dots show the correlation between changes in the UK credit-to-GDP ratio and deviations from trend estimated by an HP filter with λ=1,600 λ=25,000. Similar to the analytical result, the correlation is maximized at k=3 or k=8, 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 Figure 4. As a benchmark case, we simulate random credit-to-GDP ratios that follow a random walk, calculate the Basel gaps, and correlate the gap measure with simple time series change of the credit-to-GDP ratio. We repeat this 1,000 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 Basel gaps and time series changes, for different change periods (k). As the analytical correlations presented in Panel A of Figure 3, the simulation-based correlations 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 and $I(1)$ process, one should expect the correlation between the Basel gap and the changes in credit ratio to always follow the same pattern.

[Figure 4 here]

The remaining panels of Figure 4 provide variations of the benchmark case. First, in Panel B we simulate T=1,000 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 Basel gap and the change in credit-to-GDP ratio. In Panels C and D we study the effects of changing the HP filter smoothing parameter. In Panel C we use λ=25,000 and in Panel D λ=1,600. As in the analytical results above, a lower λ results in the Basel gap correlating more strongly with a shorter change in the credit-to-GDP ratio. The correlation is maximized at k=8 for λ=25,000 and at k=4 for λ=1,600. For the lower smoothing parameters, the range of simulated correlations is very narrow.

Finally, Panels E and F show that the close systematic relation between the Basel 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. While the correlations between the Basel gap and changes in 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 Basel gap is highly correlated with 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 on the sample size, and the smoothing parameter merely affects how long change in the underlying data the gap measure emulates. This relation breaks down when the order of integration in the underlying data is higher than one.

4 Empirical results

In this section, we show that the striking similarity between the Basel gap and the 16-quarter difference in the credit ratio holds not only for the United Kingdom, which we use above as an illustrating example, but 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.[5] The data starts at different points in time for different countries with earliest time series the extending back to the early 1950's. Data for all countries ends in

[5]The data is available for download at `https://www.bis.org/statistics/c_gaps.htm`.

2018-Q2. Table 1 lists the countries in our sample and the periods for which we observe the quarterly credit-to-GDP ratios.

[Table 1 here]

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 Basel 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 the first order. 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 any conventional level of statistical significance.

[Tables 2 and 3 here]

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.[6] Taken together, the results in Table 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 trend endpoints and changes, as documented in Sections 2 and 3 above.

In Table 4, we report the correlation coefficients between the Basel 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

[6]Table B1 in Appendix B shows that even though the ADF test is not able to reject unit root of Δy_t for Spain and Greece, the autocorrelation of Δy_t is rather low also for these countries.

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 82% (Belgium) to 96% (Denmark, Spain, and Greece). On average across all countries, the correlation is 92%. The optimal lag k is in general close to 16 and ranges between 10 and 19, with a median of k=16. Table 4 further also reports the correlation for other selected values of k, showing in general a hump-shaped pattern very similar to Figures 3 and 4.

[Tables 4 and 5 here]

Table 5 presents the correlation maximizing lags k and the corresponding maximum correlations the HP filter smoothing parameter λ is set to either 1,600 or 25,000, instead of 400,000, when calculating 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 λ=1,600, and k=8 when λ=25,000. On average, the maximum correlations are high: 0.83 for λ=1,600 and 0.88 for λ=25,000. These values are very similar to the analytical and simulation results presented in Figures 3 and 4.

[Figure 5 here]

While the patterns of correlations between the Basel gap and changes in the credit-to-GDP ratio are similar across countries, the historical developments of the credit ratio itself differs widely. Figure 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 Figure 2 for the UK. The right panels show the resulting Basel 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, that both experience prolonged periods of growth and decline in the credit ratio. The left panels show, similar to Figure 1, that the Basel 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 19990s. The credit cycles identified by the simple 16-quarter changes are thus nearly identical to the Basel gaps estimated by the one-sided HP filter.

5 Conclusion

We document that the 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 Basel 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 43 countries we investigate, the correlation between the Basel gap and the 16-quarter change in the credit-to-GDP ratio is between 0.82 and 0.96. We also conduct a Monte Carlo exercise and find similar results when applying one-sided HP filtration to simulated time-series.

We also find similar results for different values of the smoothing parameter (λ). When the smoothing parameter is decreased, the credit-gap approximates a shorter change in the credit-to-GDP ratio. Calibrating the smoothing parameter (λ) is thus effectively equivalent to calibrating the lag length over which changes are calculated.

Our results have broader implications for the application of the one-sided HP filter. We find analytically that the strong similarity between changes and deviations from trend occurs when the one-sided HP filter is applied to an $I(1)$ process. Following earlier results in the literature (King and Rebelo, 1993; Cogley and Nason, 1995), we conclude that the the HP filter does not succeed in identifying cycles from a process that has order of integration less than two.

Whether the Basel 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. What we do show is that the estimation procedure underlying the Basel gap is unnecessarily complicated and obscure. There is ultimately no need to apply complicated methods when simple changes suffice. Compared to a simple change, the one-sided HP filter is undoubtedly more difficult to understand, both to policy makers and to the broader public. We therefore recommend estimating the Basel gap more transparently by a simple change in the credit-to-GDP ratio.

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Figures and tables

Figure 1: Basel gap and 16-quarter changes. This figure plots the Basel gap (blue line) and the 16-quarter change in the credit-to-GDP ratio (red line) using data for the United Kingdom.

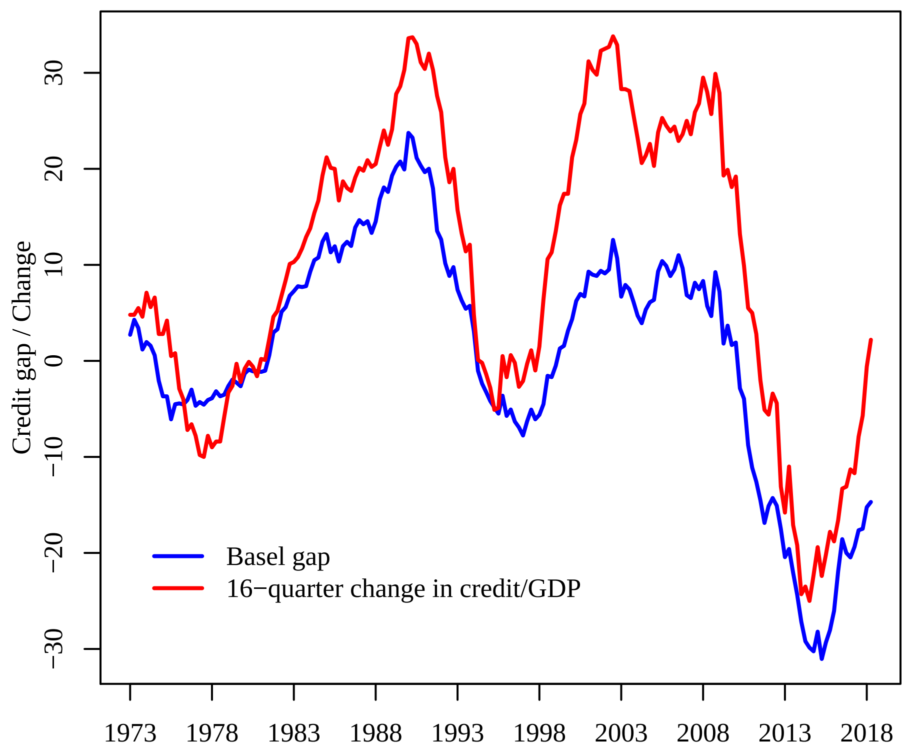

Figure 2: Two-sided and one-sided trend estimates. Panel A shows the credit-to-GDP ratio (black line) of the United Kingdom and its long-term trend estimated by the two-sided HP filter (red line). Panel B shows the credit-to-GDP ratio and trend estimated using only data up to 1988. Panel C shows trends estimated using data up to 1988, 1998, 2008, and 2018. 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.

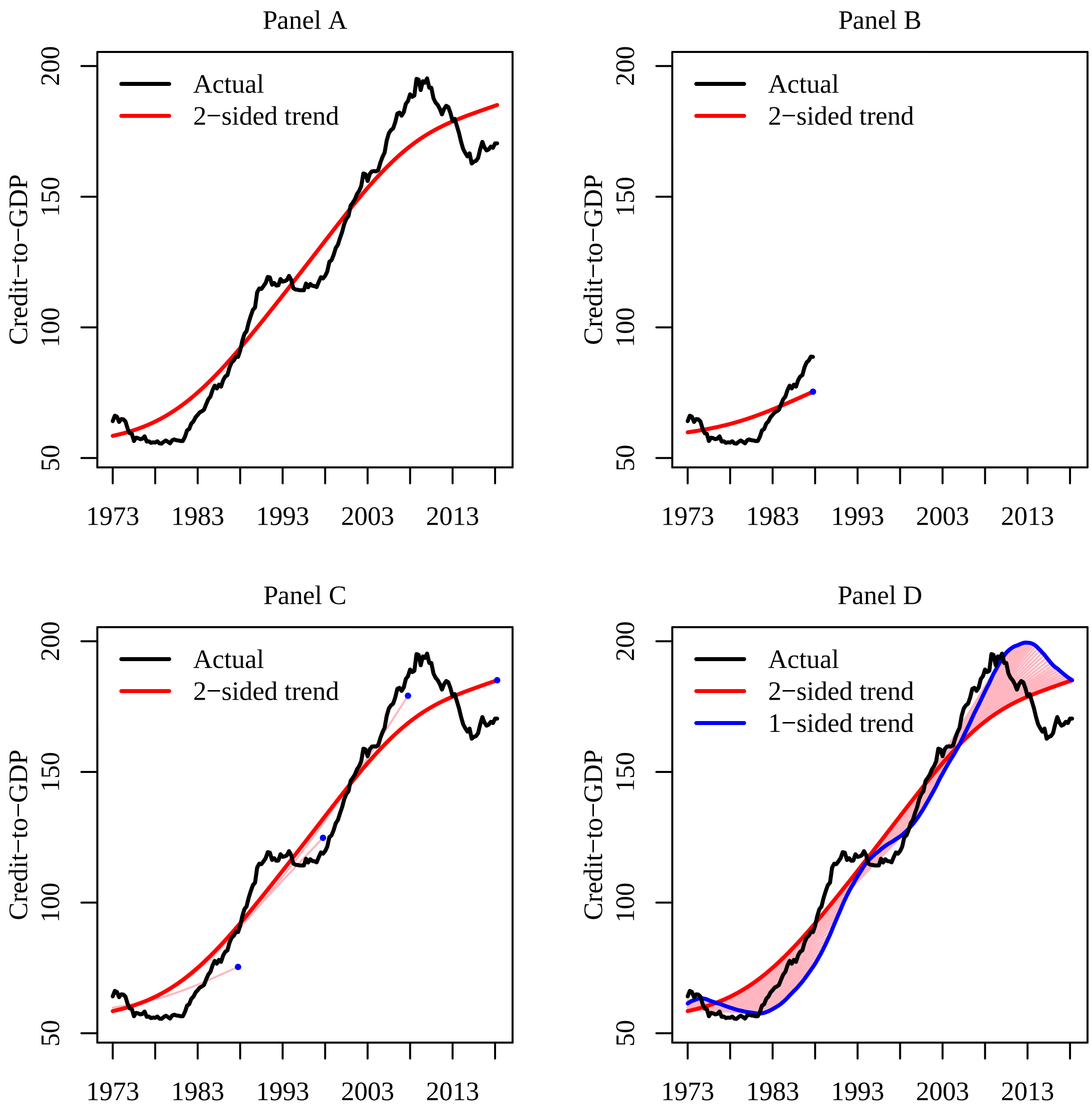

Figure 3: Correlation between Basel gap and simple changes. This figure plots the correlation coefficients between the Basel gap ($x_t = y_t - \tau_t$) and changes in the credit-to-GDP ratio ($\Delta_k y_t = y_t - y_{t-k}$). The horizontal axis depicts the number of quarters ($k = 1, \ldots, 40$) over 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 λ=400,000 in Panel A, 25,000 in Panel B, and 1,600 in Panel C.

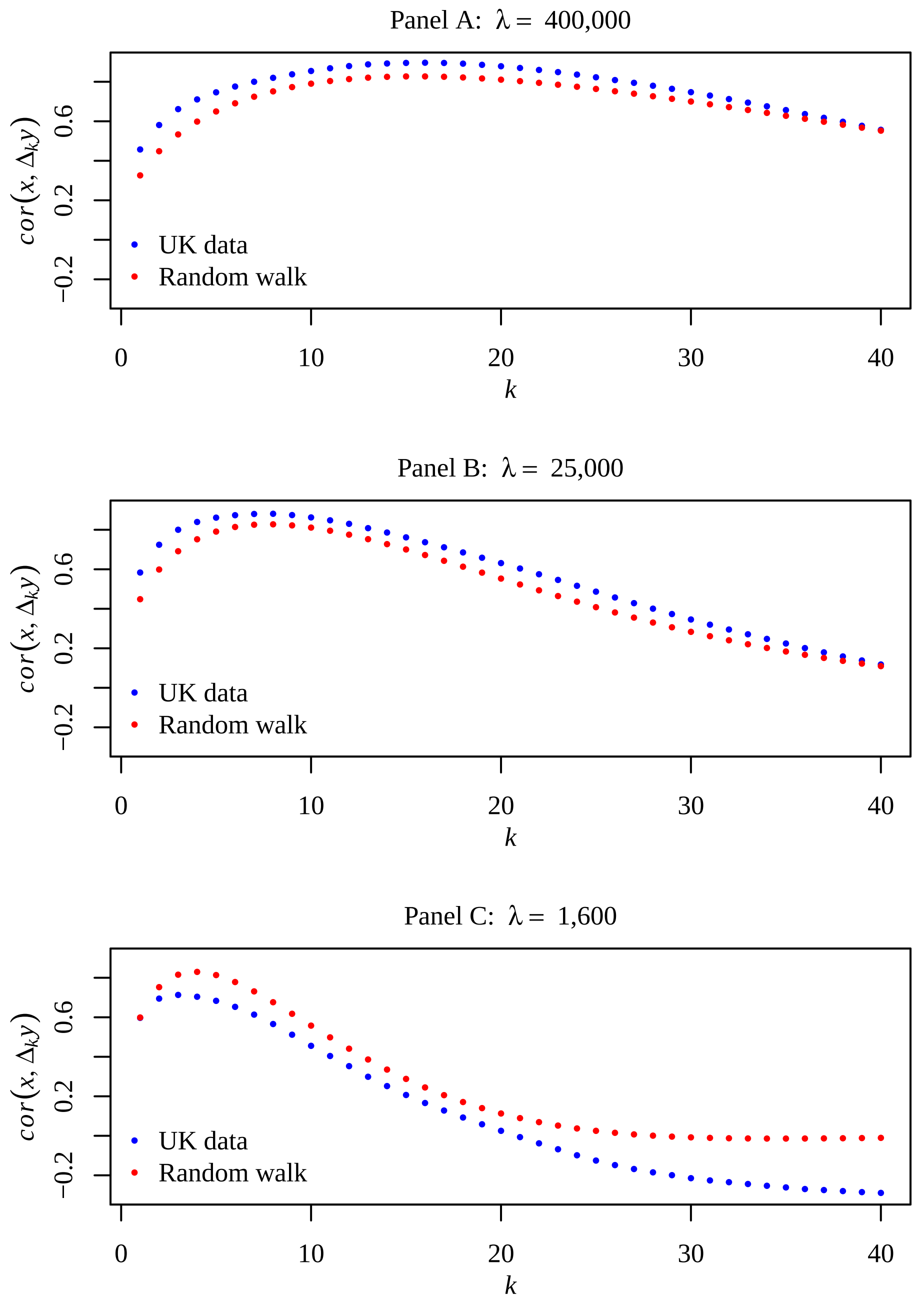

Figure 4: Simulation results. This figure plots percentiles of the correlation coefficients between the Basel gap ($x_t = y_t - \tau_t$) and changes in the credit-to-GDP ratio ($\Delta_k y_t = y_t - y_{t-k}$) based on Monte Carlo simulations with 1,000 replications. The horizontal axis depicts the number 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 ($\Delta y_t \sim N(0,1)$), λ=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=1,000) and Panels C and D are based on smaller smoothing parameters (λ=25,000 and λ=1,600, 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 ($\Delta^3 y_t \sim N(0,1)$).

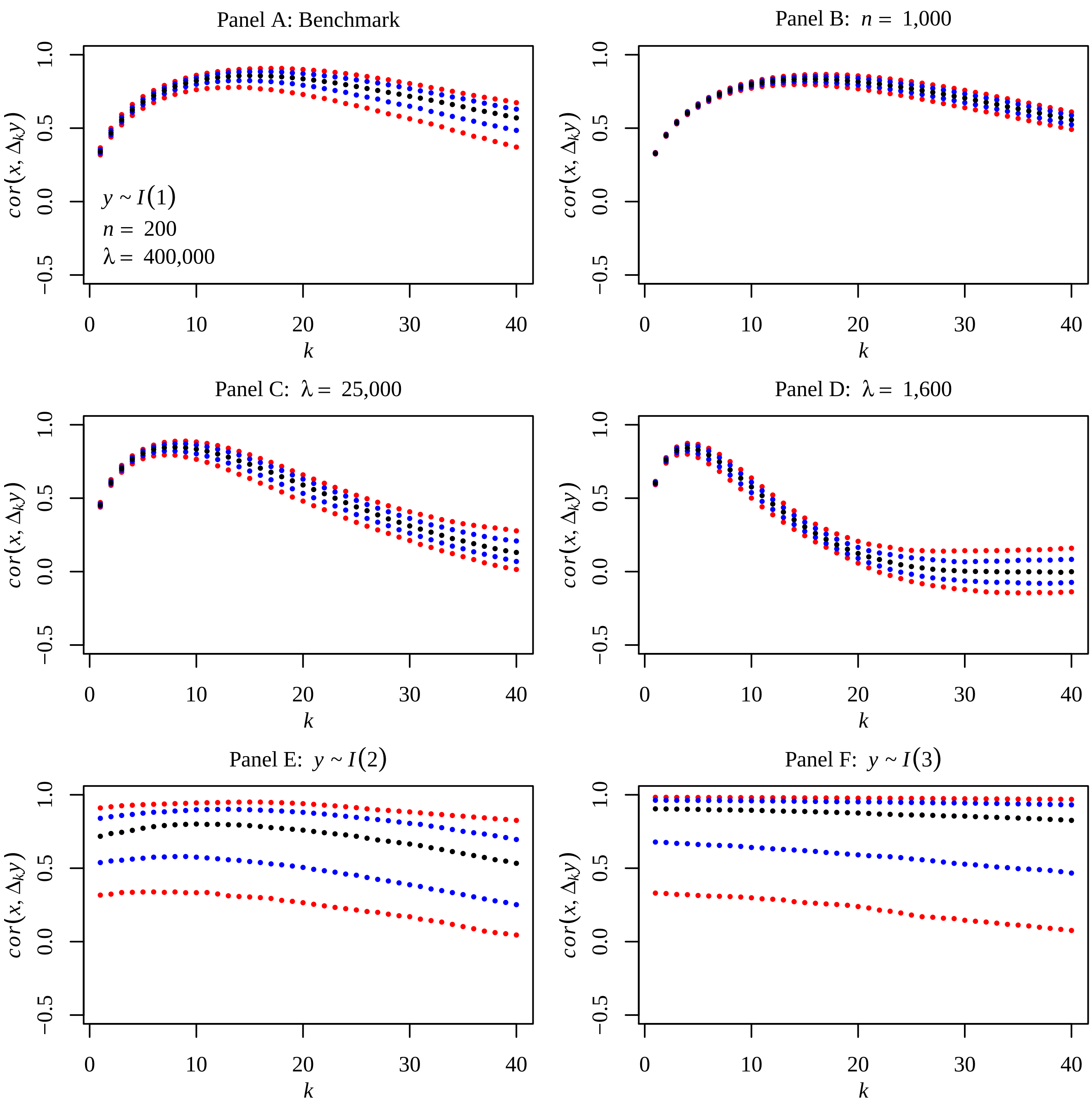

Figure 5: Other countries. This figure presents the empirical results for Italy, Japan, and Finland. The left panels show the credit-to-GDP ratios (y_t, black line) and the one-sided HP filter trends (τ_t, blue line). The right panels show the resulting Basel gaps ($x_t = y_t - \tau_t$, blue line) and the simple 16-quarter changes in the credit–to-GDP ratio ($\Delta_{16} y_t = y_t - y_{t-16}$, red line).

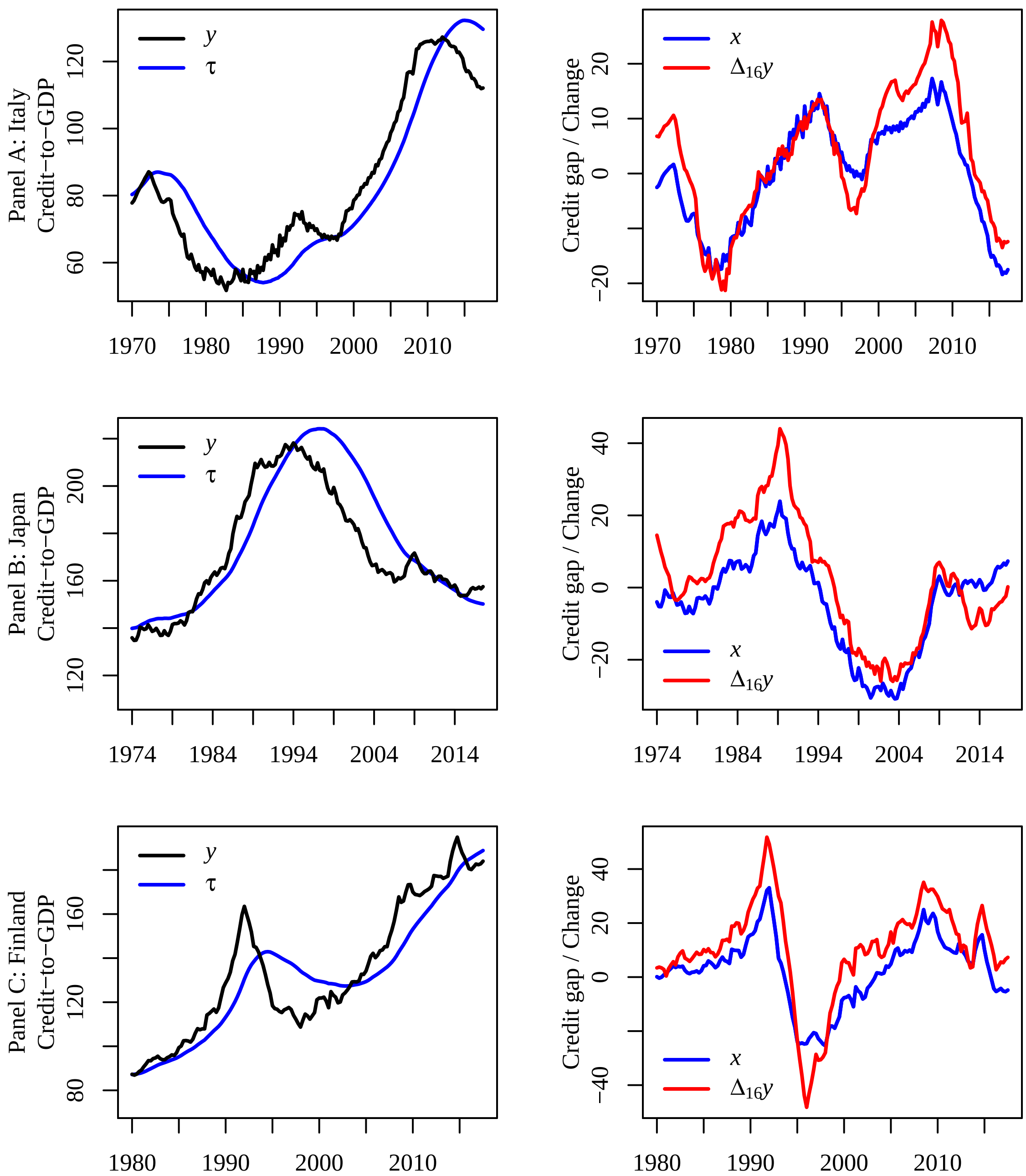

Table 1: Data. This table presents the quarterly credit-to-GDP ratio data used in the empirical analyses of this paper for 43 countries and the Euro area. *Start* gives the date of the first observation, data for all countries ends in 2018-Q2. *Obs* gives the total number of quarterly observations per country. The data are from the Bank for International Settlements.

Country		Start	Obs	Country		Start	Obs
AR	Argentina	1984-Q4	135	IL	Israel	1990-Q4	111
AT	Austria	1960-Q4	231	IN	India	1951-Q2	269
AU	Australia	1960-Q2	233	IT	Italy	1960-Q4	231
BE	Belgium	1970-Q4	191	JP	Japan	1964-Q4	215
BR	Brazil	1996-Q1	90	KR	Korea	1962-Q4	223
CA	Canada	1955-Q4	251	LU	Luxembourg	1999-Q1	78
CH	Switzerland	1960-Q4	231	MX	Mexico	1980-Q4	151
CL	Chile	1983-Q1	142	MY	Malaysia	1964-Q2	217
CN	China	1985-Q4	131	NL	Netherlands	1961-Q1	230
CO	Colombia	1996-Q4	87	NO	Norway	1960-Q4	231
CZ	Czech Republic	1993-Q1	102	NZ	New Zealand	1960-Q4	231
DE	Germany	1960-Q4	231	PL	Poland	1992-Q1	106
DK	Denmark	1966-Q4	207	PT	Portugal	1960-Q4	231
ES	Spain	1970-Q1	194	RU	Russia	1995-Q2	93
FI	Finland	1970-Q4	191	SA	Saudi Arabia	1993-Q1	102
FR	France	1969-Q4	195	SE	Sweden	1961-Q1	230
GB	United Kingdom	1963-Q1	222	SG	Singapore	1970-Q4	191
GR	Greece	1970-Q4	191	TH	Thailand	1970-Q4	191
HK	Hong Kong SAR	1978-Q4	159	TR	Turkey	1986-Q1	130
HU	Hungary	1970-Q4	191	US	United States	1952-Q1	266
ID	Indonesia	1976-Q1	170	XM	Euro area	1999-Q1	78
IE	Ireland	1971-Q2	189	ZA	South Africa	1965-Q1	214

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	-2.475	0.124	-2.191	0.211	IL	-2.341	0.161	-2.489	0.121
AT	-1.480	0.542	-1.547	0.508	IN	0.084	0.964	-0.255	0.928
AU	-0.274	0.925	-0.320	0.919	IT	-1.270	0.644	-1.672	0.444
BE	0.730	0.993	0.772	0.993	JP	-1.553	0.505	-1.861	0.351
BR	-0.950	0.767	-0.487	0.887	KR	-0.894	0.789	-1.107	0.713
CA	1.016	0.997	1.335	0.999	LU	-1.487	0.535	-1.596	0.479
CH	0.289	0.977	0.181	0.971	MX	-2.788	0.062	-2.509	0.115
CL	-0.811	0.813	-0.588	0.868	MY	-1.320	0.620	-1.438	0.563
CN	0.959	0.996	1.429	0.999	NL	-0.528	0.882	-0.568	0.874
CO	-1.399	0.579	-1.330	0.612	NO	-0.435	0.900	-0.526	0.882
CZ	-1.245	0.652	-0.917	0.779	NZ	-0.565	0.874	-0.705	0.842
DE	-2.092	0.248	-2.276	0.181	PL	-0.519	0.882	-1.107	0.711
DK	-0.698	0.844	-1.163	0.690	PT	-1.752	0.404	-1.589	0.487
ES	-1.648	0.456	-2.057	0.262	RU	-1.113	0.708	-1.154	0.691
FI	-0.518	0.884	-0.385	0.908	SA	-1.297	0.629	-1.394	0.582
FR	1.252	0.998	1.541	0.999	SE	0.026	0.959	0.682	0.992
GB	-0.405	0.905	-0.411	0.904	SG	-0.888	0.791	-0.530	0.881
GR	-1.177	0.684	-1.858	0.352	TH	-1.842	0.359	-1.903	0.330
HK	0.093	0.964	0.933	0.996	TR	2.057	1.000	2.128	1.000
HU	-1.174	0.686	-2.178	0.215	US	-1.396	0.584	-1.368	0.598
ID	-2.010	0.282	-2.270	0.183	XM	-2.013	0.281	-2.512	0.117
IE	-0.710	0.840	-0.539	0.879	ZA	-1.295	0.632	-1.429	0.568

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	-7.190	0.000	-6.931	0.000	IL	-4.017	0.002	-5.736	0.000
AT	-5.284	0.000	-3.739	0.004	IN	-4.465	0.000	-3.028	0.034
AU	-4.043	0.001	-3.978	0.002	IT	-3.492	0.009	-2.603	0.094
BE	-5.056	0.000	-6.720	0.000	JP	-4.032	0.002	-2.676	0.080
BR	-3.627	0.007	-4.954	0.000	KR	-4.992	0.000	-6.381	0.000
CA	-6.873	0.000	-6.835	0.000	LU	-3.619	0.008	-4.161	0.002
CH	-5.621	0.000	-5.543	0.000	MX	-3.975	0.002	-3.740	0.004
CL	-4.041	0.002	-3.605	0.007	MY	-4.808	0.000	-5.947	0.000
CN	-4.634	0.000	-3.715	0.005	NL	-5.189	0.000	-5.279	0.000
CO	-2.998	0.039	-3.132	0.028	NO	-4.461	0.000	-4.750	0.000
CZ	-3.960	0.002	-7.414	0.000	NZ	-4.797	0.000	-3.662	0.005
DE	-5.007	0.000	-5.021	0.000	PL	-2.839	0.056	-2.867	0.053
DK	-4.381	0.000	-2.569	0.101	PT	-3.372	0.013	-3.398	0.012
ES	-2.045	0.268	-1.797	0.381	RU	-4.085	0.002	-6.927	0.000
FI	-4.624	0.000	-7.715	0.000	SA	-4.357	0.001	-5.917	0.000
FR	-4.520	0.000	-3.458	0.010	SE	-5.299	0.000	-5.227	0.000
GB	-3.706	0.005	-4.184	0.001	SG	-4.884	0.000	-7.605	0.000
GR	-2.402	0.143	-1.312	0.624	TH	-3.154	0.024	-3.258	0.018
HK	-4.961	0.000	-5.260	0.000	TR	-4.446	0.000	-6.384	0.000
HU	-3.170	0.023	-2.499	0.117	US	-3.701	0.005	-3.675	0.005
ID	-6.049	0.000	-6.025	0.000	XM	-2.802	0.063	-4.088	0.002
IE	-4.351	0.000	-12.493	0.000	ZA	-5.146	0.000	-5.912	0.000

Table 4: Empirical results. This table reports correlations between Basel 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 Basel 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.

	k	$Cor(k)$	$Cor(4)$	$Cor(8)$	$Cor(16)$	$Cor(24)$	$Cor(32)$	$Cor(40)$
AR	18	0.871	0.657	0.780	0.866	0.752	0.655	0.546
AT	17	0.942	0.696	0.845	0.937	0.887	0.778	0.747
AU	16	0.892	0.645	0.792	0.892	0.828	0.694	0.539
BE	11	0.821	0.680	0.802	0.817	0.709	0.550	0.455
BR	11	0.948	0.743	0.902	0.897	0.690	0.589	0.334
CA	17	0.928	0.651	0.826	0.928	0.861	0.757	0.655
CH	17	0.899	0.661	0.809	0.898	0.843	0.734	0.653
CL	17	0.891	0.620	0.787	0.890	0.839	0.682	0.441
CN	17	0.914	0.661	0.853	0.911	0.830	0.793	0.625
CO	11	0.953	0.704	0.882	0.850	0.801	0.700	0.684
CZ	13	0.973	0.754	0.903	0.962	0.841	0.650	0.433
DE	19	0.947	0.724	0.865	0.940	0.920	0.826	0.727
DK	17	0.957	0.785	0.901	0.957	0.902	0.775	0.585
ES	13	0.964	0.896	0.946	0.956	0.892	0.780	0.632
FI	17	0.934	0.647	0.819	0.933	0.895	0.781	0.640
FR	17	0.939	0.695	0.849	0.938	0.880	0.754	0.655
GB	16	0.896	0.711	0.820	0.896	0.836	0.712	0.557
GR	10	0.973	0.919	0.969	0.955	0.875	0.744	0.607
HK	18	0.949	0.701	0.850	0.942	0.903	0.874	0.859
HU	17	0.975	0.793	0.909	0.974	0.940	0.836	0.692
ID	17	0.855	0.632	0.774	0.855	0.811	0.747	0.655
IE	12	0.915	0.775	0.894	0.909	0.840	0.690	0.488

Table continues on the next page

Table 4 continues

	k	$Cor(k)$	$Cor(4)$	$Cor(8)$	$Cor(16)$	$Cor(24)$	$Cor(32)$	$Cor(40)$
IL	16	0.961	0.729	0.897	0.961	0.922	0.872	0.851
IN	14	0.937	0.771	0.896	0.933	0.870	0.768	0.612
IT	13	0.925	0.813	0.896	0.919	0.852	0.726	0.570
JP	14	0.895	0.769	0.859	0.893	0.855	0.775	0.666
KR	15	0.909	0.631	0.811	0.909	0.854	0.697	0.461
LU	12	0.911	0.701	0.831	0.811	0.483	0.739	0.808
MX	14	0.934	0.731	0.859	0.929	0.839	0.693	0.553
MY	15	0.909	0.656	0.814	0.908	0.862	0.784	0.629
NL	12	0.877	0.682	0.819	0.855	0.736	0.527	0.320
NO	17	0.897	0.645	0.811	0.896	0.854	0.742	0.566
NZ	16	0.861	0.639	0.778	0.861	0.781	0.639	0.494
PL	12	0.910	0.731	0.873	0.877	0.713	0.593	0.313
PT	15	0.949	0.801	0.898	0.949	0.899	0.796	0.682
RU	11	0.926	0.733	0.902	0.839	0.652	0.646	0.487
SA	12	0.954	0.679	0.877	0.898	0.666	0.755	0.802
SE	16	0.920	0.668	0.831	0.920	0.858	0.704	0.540
SG	16	0.928	0.655	0.827	0.928	0.876	0.797	0.613
TH	18	0.947	0.711	0.837	0.944	0.915	0.815	0.671
TR	16	0.948	0.705	0.873	0.948	0.907	0.800	0.718
US	18	0.958	0.714	0.842	0.955	0.923	0.809	0.687
XM	18	0.963	0.799	0.913	0.961	0.923	0.898	0.946
ZA	15	0.911	0.632	0.818	0.907	0.749	0.592	0.529
Median	16	0.928	0.702	0.850	0.915	0.854	0.745	0.619

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.

	$\lambda = 1{,}600$		$\lambda = 25{,}000$		$\lambda = 400{,}000$	
	k	$Cor(k)$	k	$Cor(k)$	k	$Cor(k)$
AR	4	0.866	8	0.832	18	0.871
AT	5	0.824	9	0.926	17	0.942
AU	4	0.838	9	0.907	16	0.892
BE	4	0.847	7	0.814	11	0.821
BR	4	0.860	7	0.926	11	0.948
CA	4	0.863	8	0.902	17	0.928
CH	4	0.839	9	0.880	17	0.899
CL	4	0.848	8	0.913	17	0.891
CN	4	0.845	7	0.903	17	0.914
CO	4	0.799	6	0.872	11	0.953
CZ	3	0.666	6	0.843	13	0.973
DE	3	0.729	7	0.814	19	0.947
DK	3	0.752	7	0.887	17	0.957
ES	2	0.682	5	0.873	13	0.964
FI	4	0.843	8	0.905	17	0.934
FR	3	0.773	7	0.826	17	0.939
GB	3	0.713	8	0.881	16	0.896
GR	3	0.655	4	0.798	10	0.973
HK	5	0.812	7	0.883	18	0.949
HU	3	0.736	7	0.890	17	0.975
ID	4	0.886	7	0.845	17	0.855
IE	4	0.833	7	0.854	12	0.915

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Table 5 continues

	$\lambda = 1{,}600$		$\lambda = 25{,}000$		$\lambda = 400{,}000$	
	k	Cor(k)	k	Cor(k)	k	Cor(k)
IL	3	0.747	5	0.815	16	0.961
IN	3	0.726	6	0.804	14	0.937
IT	3	0.701	7	0.823	13	0.925
JP	3	0.618	6	0.720	14	0.895
KR	4	0.869	9	0.929	15	0.909
LU	4	0.890	11	0.923	12	0.911
MX	3	0.833	9	0.948	14	0.934
MY	4	0.835	8	0.857	15	0.909
NL	4	0.889	9	0.921	12	0.877
NO	4	0.866	8	0.882	17	0.897
NZ	4	0.807	9	0.893	16	0.861
PL	4	0.909	9	0.925	12	0.910
PT	3	0.780	7	0.862	15	0.949
RU	5	0.925	9	0.937	11	0.926
SA	4	0.940	9	0.945	12	0.954
SE	4	0.809	8	0.863	16	0.920
SG	4	0.832	9	0.934	16	0.928
TH	3	0.759	8	0.870	18	0.947
TR	3	0.786	6	0.800	16	0.948
US	3	0.769	8	0.938	18	0.958
XM	4	0.829	9	0.936	18	0.963
ZA	4	0.895	9	0.922	15	0.911
Median	4	0.830	8	0.883	16	0.928

Appendix A 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 A1 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:

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

Table A2 reports the correlations between x_T and $\Delta_k y_T$ for k=1,. . . ,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 Figure 3. The next three columns show that the correlations are nearly identical when the sample size is increased to T=1,000. This result is expected, since the weights as reported in A1 are not sensitive to T. The final columns of Table A2 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).

Table A1: 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.

	λ= 400,000			λ= 25,000			λ= 1,600		
t	T=100	T=200	T=1000	T=100	T=200	T=1000	T=100	T=200	T=1000
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 A2: Correlations. This table reports $cor\left(x_T, \Delta_k y_T\right)$, the correlation between the end-point of a time-series y_T in deviation from trend and in deviation from its k-order lag, for k=1,...,20. The correlation is derived using the weights cacluated following Cornea-Madeira (2017), for different values of the smoothing parameter λ and sample size T, see Table A1. 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=1000			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	0.727	0.8497	0.8761
6	0.6909	0.8141	0.7785	0.6908	0.8141	0.7785	0.7723	0.8744	0.839
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	0.835	0.8877	0.7363
9	0.7731	0.8222	0.6176	0.773	0.8222	0.6176	0.8555	0.8823	0.6812
10	0.7903	0.811	0.5577	0.7902	0.811	0.5577	0.8704	0.8718	0.6283
11	0.8037	0.795	0.4983	0.8036	0.795	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	0.825	0.7273	0.3352	0.825	0.7273	0.3352	0.893	0.8118	0.4695
15	0.8271	0.7003	0.288	0.827	0.7003	0.288	0.8932	0.7977	0.4454
16	0.8271	0.672	0.2448	0.8271	0.672	0.2448	0.8923	0.7855	0.4269
17	0.8253	0.6429	0.2058	0.8252	0.6429	0.2058	0.891	0.7754	0.4135
18	0.8218	0.6131	0.171	0.8217	0.6131	0.171	0.8895	0.7676	0.4043
19	0.8168	0.583	0.1401	0.8168	0.583	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

Appendix B Supplementary empirical results

Table B1: AR(4) coefficients. This table presents the coefficient estimates of an AR(4) model estimated on the differences of the credit-to-GDP ratios. Coefficient standard errors are reported in parenthesis.

	Δy_1	Δy_2	Δy_3	Δy_4		Δy_1	Δy_2	Δy_3	Δy_4
AR	-0.176	-0.230	-0.383	0.056	DE	0.098	0.190	-0.083	0.394
	(0.086)	(0.082)	(0.082)	(0.087)		(0.060)	(0.060)	(0.061)	(0.060)
AT	-0.061	0.063	-0.079	0.374	DK	0.232	0.321	-0.088	0.173
	(0.061)	(0.061)	(0.061)	(0.061)		(0.068)	(0.070)	(0.070)	(0.068)
AU	0.299	0.196	0.002	0.191	ES	0.219	0.334	-0.048	0.360
	(0.064)	(0.067)	(0.067)	(0.065)		(0.067)	(0.069)	(0.069)	(0.068)
BE	0.114	0.336	-0.164	0.029	FI	0.489	0.041	-0.011	0.032
	(0.072)	(0.072)	(0.072)	(0.073)		(0.073)	(0.081)	(0.081)	(0.073)
BR	0.113	0.196	-0.061	0.006	FR	0.095	0.172	-0.115	0.352
	(0.105)	(0.108)	(0.110)	(0.110)		(0.067)	(0.068)	(0.067)	(0.070)
CA	0.219	0.236	-0.114	0.071	GB	0.062	0.049	0.145	0.298
	(0.063)	(0.064)	(0.065)	(0.063)		(0.064)	(0.063)	(0.064)	(0.066)
CH	0.144	0.204	-0.141	0.199	GR	0.097	0.286	0.158	0.250
	(0.064)	(0.064)	(0.064)	(0.065)		(0.070)	(0.069)	(0.070)	(0.071)
CL	0.293	-0.015	0.031	0.184	HK	0.155	-0.010	0.119	0.122
	(0.083)	(0.087)	(0.087)	(0.083)		(0.079)	(0.079)	(0.079)	(0.078)
CN	0.168	0.014	0.060	0.117	HU	0.072	0.084	-0.072	0.157
	(0.088)	(0.093)	(0.095)	(0.094)		(0.072)	(0.071)	(0.072)	(0.071)
CO	0.470	0.257	-0.118	0.119	ID	0.272	-0.092	0.113	-0.295
	(0.106)	(0.116)	(0.117)	(0.108)		(0.073)	(0.076)	(0.075)	(0.072)
CZ	0.228	0.021	0.162	-0.038	IE	0.063	-0.047	0.066	0.082
	(0.099)	(0.100)	(0.100)	(0.098)		(0.073)	(0.073)	(0.073)	(0.073)

Table continues on the next page

Table B1 continues

	Δy_1	Δy_2	Δy_3	Δy_4		Δy_1	Δy_2	Δy_3	Δy_4
IL	0.183	0.141	-0.166	0.028	PL	0.457	-0.025	0.045	-0.006
	(0.095)	(0.096)	(0.096)	(0.095)		(0.097)	(0.107)	(0.108)	(0.099)
IN	-0.108	0.019	-0.051	0.560	PT	0.167	0.190	-0.014	0.360
	(0.051)	(0.051)	(0.051)	(0.051)		(0.061)	(0.062)	(0.062)	(0.061)
IT	0.095	0.157	-0.137	0.625	RU	0.160	-0.117	0.052	0.137
	(0.051)	(0.050)	(0.050)	(0.050)		(0.104)	(0.104)	(0.104)	(0.103)
JP	0.342	-0.121	0.124	0.371	SA	0.451	-0.024	-0.057	0.015
	(0.063)	(0.067)	(0.067)	(0.063)		(0.099)	(0.108)	(0.108)	(0.099)
KR	0.240	0.272	-0.044	0.065	SE	0.217	0.193	0.078	0.160
	(0.067)	(0.069)	(0.069)	(0.067)		(0.065)	(0.068)	(0.068)	(0.067)
LU	0.547	0.076	-0.019	-0.237	SG	0.206	0.136	0.049	-0.051
	(0.110)	(0.129)	(0.129)	(0.111)		(0.073)	(0.075)	(0.075)	(0.073)
MX	0.186	0.255	-0.017	0.160	TH	0.162	0.169	0.188	0.181
	(0.080)	(0.082)	(0.082)	(0.080)		(0.071)	(0.070)	(0.070)	(0.071)
MY	0.435	0.108	0.113	-0.035	TR	0.233	0.193	-0.236	0.075
	(0.068)	(0.074)	(0.074)	(0.068)		(0.088)	(0.088)	(0.088)	(0.088)
NL	0.195	0.147	-0.146	0.202	US	0.204	0.346	-0.103	0.354
	(0.066)	(0.066)	(0.067)	(0.066)		(0.057)	(0.059)	(0.059)	(0.058)
NO	0.314	0.031	0.284	-0.028	XM	0.110	0.218	-0.075	0.226
	(0.066)	(0.066)	(0.066)	(0.066)		(0.110)	(0.109)	(0.112)	(0.112)
NZ	-0.057	0.115	0.144	0.247	ZA	0.230	0.129	0.120	-0.089
	(0.064)	(0.063)	(0.064)	(0.064)		(0.068)	(0.069)	(0.070)	(0.068)