Erasmus University Rotterdam

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Master's Thesis International Economics

# Credit gaps and economic growth


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## Abstract


This thesis investigates the effect of two credit gaps on economic growth. The first gap, the GDP credit gap, is the growth in real credit unexplained by changes in real GDP. Using a data set of 36 countries and taking into account the presence of cross-sectional dependence in the data, the estimated effect is insignificant. As an alternative, the Beveridge-Nelson decomposition is used to create another credit gap, the BN credit gap. The BN credit gap is equal to the cycle component of this decomposition and is obtained after estimating an autoregressive model for real credit in state space form with the Kalman Filter. This gap also has an insignificant effect on economic growth. Moreover, a Granger causality test indicates that real GDP influences the BN credit gap and not the other way around. The nonparametric block bootstrap method applied to the unbalanced data to estimate standard errors is not completely random, other methods might lead to better approximations.



*Keywords:* credit gap • economic growth • cross-sectional dependence • nonparametric bootstrap

# Contents

# 1 Introduction

Credit plays a key role in our economy. It allows people and businesses to finance their expenditures and investments, hence fosters economic growth. But when credit grows excessively it has a negative impact on economic growth and could lead to a recession (Kaminsky & Reinhart, 1999). A good example is the Great Recession which was preceded by a large increase in US housing credit. From 2002Q1 to 2008Q1 the total mortgage debt outstanding increased by more than 90 percent while gross domestic product (GDP) grew by just 35 percent[1]. More generally, Jordà et al. (2013) provides evidence that credit-intensive expansions result in deeper recessions and slower recoveries. Although credit growth has a negative effect on recessions, expansions without credit are characterized by below-average growth rates (Abiad et al., 2011). The optimal credit provision should thus strike a balance between these two effects.

From a policy perspective, as financial cycles are strongly related to business cycles, the challenge is to provide the economy with the right amount of credit (World Bank, 2013). The build-up of systemic risk, created by credit expansions, will eventually cause an economic downturn when materialized. Therefore, there is more attention for the downside than the upside risks of capital flows. As stated in a joint report of FSB, IMF and BIS (2011), macroprudential policy should focus primarily on limiting systemic risk or system-wide financial risk. During expansions systemic risk increases due to more leverage, rising asset prices and maturity mismatches with financial distress during downturns as a consequence. If the goal is to decrease systemic risk, then credit growth should be kept at a minimum. However, this is not in line with the positive effect of credit growth on economic growth during expansions.

To determine whether the economy is provided with the right amount of credit, regulators have relied on the credit-to-GDP ratio since Basel III. Deviations from the long-run trend in the credit-to-GDP ratio, known as the credit gap, are used to identify the build-up of systemic risk and to predict credit busts. However, this method has been criticized because of the Hodrick-Prescott filtering technique required to obtain the long-run trend and its behavioral properties. As a response, the literature has proposed alternative ways to create a credit gap. One such measure is equilibrium credit developed by Buncic and Melecky (2014). Their paper develops a structural approach to estimate equilibrium credit, an estimate of credit based on the long-run relation between credit and the GDP components: real GDP and the GDP deflator. They also argue that using the standard credit-to-GDP ratio in studies investigating the relation between credit provision and economic growth is too restrictive in the sense that they imply a unit price and income elasticity of credit, which is rejected by the data. Deviations from the equilibrium are regarded as either excessive or lacking and summarized by the credit gap, which, in their case, is the difference between the amount of credit currently outstanding and the equilibrium. However, they do not investigate the relation between this GDP based credit gap and economic growth. Therefore, the research question is as follows

What is the effect of the credit gap on economic growth?

[1]See https://www.federalreserve.gov/releases/z1/default.htm, "Financial Accounts of the United States", and https://fred.stlouisfed.org/series/GDP, "Gross Domestic Product", accessed: 19-05-2020.

This paper makes several contributions to the existing literature. First, two new credit gaps have been used. Second, the data covers a large panel of 36 countries with more than 4500 observations. Third, throughout the paper the presence of cross-sectional dependence has been taken into account. Not only in the unit root tests and cointegration test, but also in the bootstrap algorithm and when estimating the effect of the gaps on economic growth by using the common correlated effects mean group estimator. Finally, the nonparametric continuous block bootstrap used to calculate standard errors has been adjusted to be able to simulate unbalanced panel data sets. The adjustments restrict the available blocks to be selected by the algorithm when time passes.

The results of this paper can be summarized as follows. First, because economic growth is approximated by real GDP, the relation between real GDP and real credit is investigated instead of the relation between real GDP, the GDP deflator and nominal credit which is the way Buncic and Melecky (2014) defined equilibrium credit. Moreover, a cointegration test ruled out the existence of a long-run relation between real credit and real GDP such that a new credit gap has been defined. This GDP credit gap is the first difference of real credit unexplained by past changes in real GDP. The effect of this credit gap on real GDP is insignificant.

As an alternative to the GDP credit gap, the Beveridge-Nelson (BN) decomposition is used to divide the real credit series in a trend and cycle component. These two components are obtained with an autoregressive state space model for the first difference of real credit, which is estimated using the Kalman Filter. The BN credit gap is then defined as the obtained cycle component. This credit gap is more persistent than the GDP credit gap with longer periods being either positive or negative but still more volatile than the regulatory Basel credit gap. Similar to the GDP credit gap, the effect of the BN credit gap on economic growth is also insignificant. The BN credit gap has additionally been tested for Granger causing real GDP by determining whether the BN credit gap improves forecasting real GDP out-of-sample upon a fully autoregressive model. However, the BN credit gap does not provide a significant improvement whereas adding real GDP to a forecasting model for the BN credit gap does lead to better models. Granger causality thus seems to run in the other direction which makes the BN credit gap as an instrument in determining credit provision questionable.

The structure of this paper is outlined as follows. Section 2 provides an overview of the existing literature on the effects of credit and further explains the regulatory credit gap of Basel III. In Section 3 the approach of Buncic and Melecky (2014) is explained in more detail. Section 4 summarizes the data set used and conducts tests on unit roots and cointegration after which Section 5 describes the methodology. It shows how the GDP and BN credit gaps are defined, how the effect of these credit gaps on real GDP are estimated and explains the bootstrap method used to approximate standard errors in the regressions. Section 6 gives an overview of the simulated data of the bootstrap and reports the results of the GDP and BN credit gap. A summary of the results, its shortcomings and suggestions for further research can be found in Section 7.

# 2 Literature review

## 2.1 Relation between credit and economic growth

The relation between economic growth and credit is an active research topic. Recently, Dolores Gadea Rivas et al. (2020) has investigated the role of credit growth on economic growth over the full business cycle. They separate the expansion and recession periods and find a trade-off with the level of credit growth. Large credit growth is usually followed by deeper recessions but also increases the duration of the expansion. Consequently, trying to mitigate systemic risk by reducing credit growth will negatively affect economic growth in the expansion. Moreover, they show that intermediate levels of credit growth (in the second and third quartile), measured in terms of variation in the credit-to-GDP ratio, maximizes long term economic growth. Figure 1 shows the annual variation in the credit-to-GDP ratio for the Euro area and the US with the band representing the intermediate credit growth rates. The excessive credit buildup of the Great Recession is clearly outside this band.

Because credit is a very broad term, most papers investigating the growth-debt nexus focus on either private or public credit. Where Dolores Gadea Rivas et al. (2020) uses private credit, the paper of Reinhart and Rogoff (2010) looks at public debt. They find a nonlinear negative effect of the debt-to-GDP ratio on real GDP growth. As long as the debt-to-GDP ratio is less than 90 percent the effect is rather absent, for higher values the median and average real GDP growth rates decrease 1 and 4 percentage points per annum. These results hold for advanced and emerging economies. In a follow-up research, Chudik et al. (2017) provides a formal statistical model for the existence of a threshold effect of public debt on economic growth. Although no homogeneous threshold effect is found, there is a statistically significant negative long-run relation between debt-to-GDP and economic growth. Another important contribution of this paper is that they control for cross-sectional dependence which affects the results by common unobserved factors and their spillovers. These factors could be global business cycles, commodity prices or cross-country capital flows (Chudik et al., 2017).

Ranciere et al. (2008) shows there is a positive link between systemic risk and GDP growth. Countries that experienced financial crises have grown faster than countries with stable financial conditions. Instead of using a credit-to-GDP ratio, they innovate by using the skewness of the credit growth distribution as a measure for systemic risk. This is because rare crisis events tilt the distribution to the left such that crisis prone countries have lower skewness. The positive relation of systemic risk and GDP growth is explained by a lower cost of capital and relaxing borrowing constraints due to increasing systemic risk, which leads to more investments and growth. The skewness of credit growth is associated with financial liberalization, where more liberal financial markets have a negative effect on skewness (Popov, 2014). This is confirmed by Rancière and Tornell (2016) who derives that financial liberalization increases allocative efficiency of resources and growth but only when standard forms of debt are allowed to be issued.

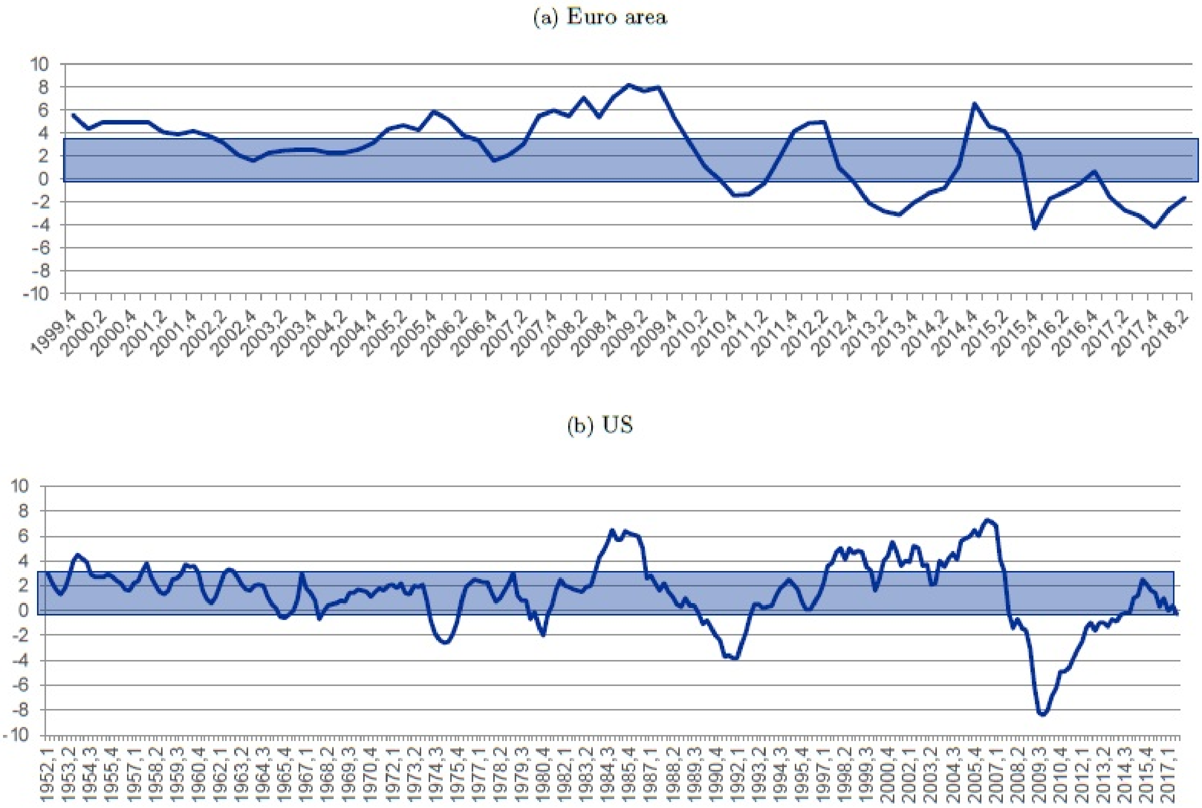


**Figure 1:** Annual variation in the credit-to-GDP ratio of (a) the Euro area and (b) the US. The band shows the intermediate variation, second and third quartile, of the credit-to-GDP ratio. Source: Dolores Gadea Rivas et al. (2020)

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## 2.2 Explanations for the existing trade-off

For the vanishing growth effect of financial depth, measured by the credit-to-GDP ratio, as shown in Reinhart and Rogoff (2010) where too much financial depth deteriorates economic growth, several reasons are given by the literature. First, there is a difference in the effect of credit on growth between firm credit and household credit (Loayza et al., 2017). Firm credit stimulates growth more than household credit. Moreover, according to Chakraborty et al. (2018) household credit crowds-out firm credit and a higher household credit-to-GDP ratio predicts lower GDP growth and higher unemployment (Mian et al., 2017). Second, more financial depth allows the economy to reach a higher steady state such that economic growth is temporarily boosted towards the improved steady state (Loayza et al., 2017). Levchenko et al. (2009) shows that financial liberalization lowers industry mark-ups and hence the economy is able to achieve a less distorted economic state. Lastly, the vanishing effect of financial depth can be explained by the negative relation between the growth rate of the financial sector and the growth rate of the real economy (Cecchetti & Kharroubi, 2015). This is because of competing resources where R&D-intensive or external finance dependent firms are especially hurt in productivity growth when finance booms.

## 2.3 Other effects of credit growth

To go beyond the effect of credit on GDP, several studies have investigated the impact of the credit boom and bust of the Great Recession in the US from a socio-economic perspective. For example, Kumhof et al. (2015) observes a rise in both household credit and income inequality prior to the financial crisis, which led to low income groups being increasingly indebted. The large savings at the top of the income distribution were used as loans to the bottom part to mitigate their relative fall in income, increasing financial instability. Moreover, over the 2000-2010 period, the share of wealth of the wealthiest 1 percent rose from 32% to 40% (Loayza et al., 2017).

Another area where credit has played a role is in neighborhood demographics. Ouazad and Rancière (2016) provide evidence that during 2000-2010 US segregation has increased in metropolitan areas with a higher relaxation of borrowing constraints. Specifically, Figure 2 shows the change in the fraction of whites as a function of the fraction of blacks in 2000 for metropolitan areas with either a small or large increase in mortgage approval rates. In areas with high approval rates, white households moved to neighborhoods with a small black minority (mB) and left neighborhoods with larger fractions of blacks (Mixed & MB). These trends are significantly different from the areas where the approval rate was lower.

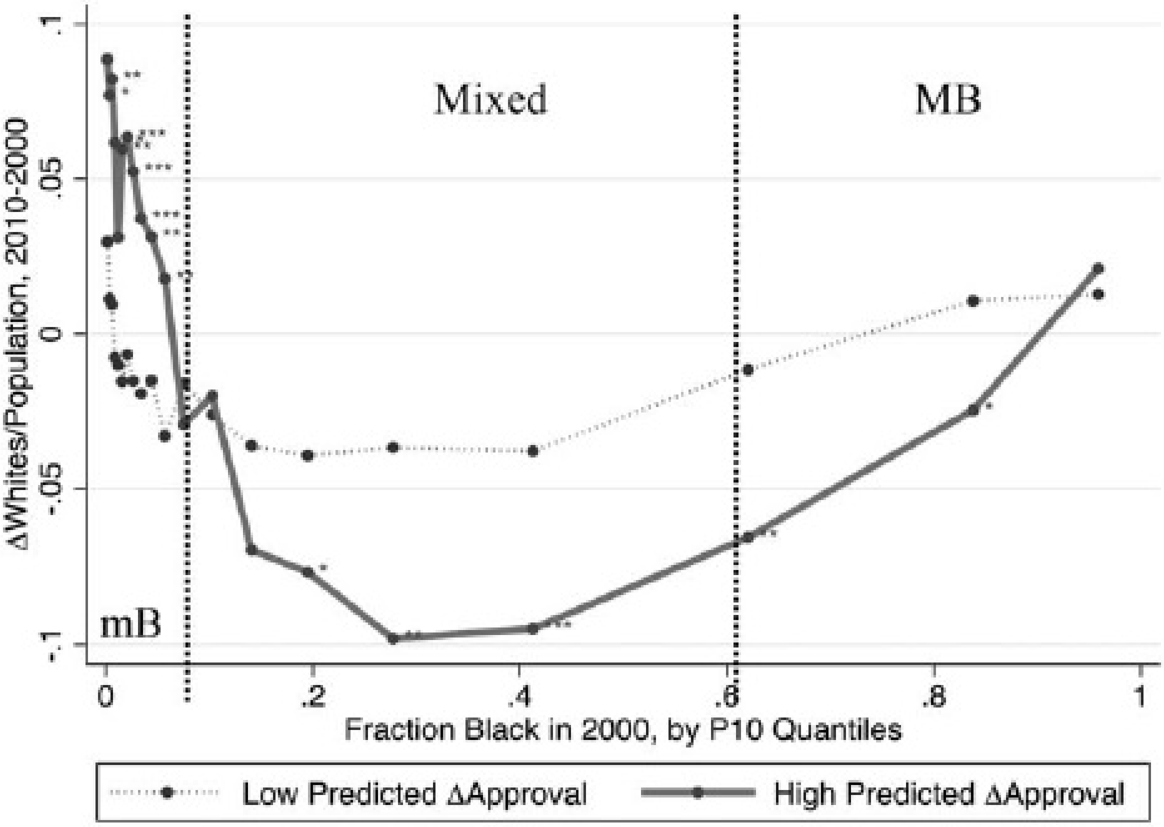


**Figure 2:** Tract-level white population change for different black fractions in tract. mB: fraction black below 10%, Mixed: between 10% and 60%, MB: above 60%. Significance of ***1%, **5%, or *10% of the F-test that the coefficient for high-liquidity metropolitan areas is equal to the coefficient for low-liquidity metropolitan areas. Source: Ouazad and Rancière (2016)

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## 2.4 The credit-to-GDP ratio and Basel III

To steer the financial and economic cycle and control systemic risk, the Basel Committee on Banking Supervision (BCBS) introduced a countercyclical capital buffer in Basel III (BCBS, 2010). Borio et al. (2010) investigates different possible schemes and examines the usefulness of several variables in determining countercyclical capital. A countercyclical scheme should by definition build a buffer during the expansion phase and fall in the release phase when the banking sector is in distress. It must preferably be build upon the existing minimum capital requirements such that these do not lose their credibility (Borio et al., 2010). Furthermore, the scheme can be bank-specific or system-wide, where bank-specific schemes allow different buffers for different banks based on their performance or risks and system-wide buffers use a common approach. The system-wide scheme seems more suitable given the objective of protection against procyclical shocks and the fact that idiosyncratic factors are not very persistent causing a lot of changes to the buffer for each bank individually (Borio et al., 2010).

The performance of various groups of variables is assessed during both phases of the cycle (buildup & release). These variables relate to macroeconomic aggregates, banking activity, and cost of funding. The credit-to-GDP ratio has the lowest signal-to-noise ratio meaning that it accurately produces crisis signals and the least false signals relative to the other variables considered (Borio et al., 2010). It also increases in a relatively stable manner during the expansion. Hence, it performs well in the buildup phase when systemic risk is rising. Additional advantages are its simplicity and data availability. For other variables, like credit spreads and bank losses, there is not much data but these variables could still be useful as timing indicators to release the buffer (Borio et al., 2010). Finally, a through-the-cycle buffer is less volatile and less cyclical than a point-in-time buffer increasing the effectiveness of the buffer buildup during the expansion period (Borio et al., 2010). Because of these reasons, Basel III suggests using the credit-to-GDP ratio when making buffer decisions (BCBS, 2010). Specifically, a credit gap is advised to calculate as the difference between the current credit-to-GDP ratio and the long term credit-to-GDP trend obtained with the Hodrick-Prescott filter. The credit gap, combined with a lower and upper threshold, is then used to create a buffer. Buncic and Melecky (2014) distinguishes their method by not relying on nominal GDP but allows credit to respond differently to changes in the components of nominal GDP: real GDP and the GDP deflator.

## 2.5 Limitations of the Basel III credit gap

Baba et al. (2020) has recently reviewed the use of the credit gap as suggested by the Basel III regulation. They list a number weaknesses:

-An above trend credit-to-GDP ratio does not necessarily result in a financial bust. A rising credit-to-GDP ratio could also indicate increasing financial deepening or policy changes that intentionally lead to more financial intermediation. The credit-to-GDP gap is thus not informative enough to indicate excessive credit growth.

-The credit gap shows countercyclical movements. During a credit boom the gap rises and then increases further in the economic downturn as GDP falls more than credit. The gap would then suggest to further tighten macroprudential policy resulting in more adverse effects for the economy. This is in line with Borio et al. (2010) highlighting the performance of the credit-to-GDP ratio during the build-up phase.

-The credit gap follows the boom with a few years lag. Therefore, after a bust the credit gap stays negative for an extended period of time while the economy is already recovering for a few years indicating that systemic risk is rising again. In the recovery the credit gap is expected to be positive again but it is not. Consequently, the credit gap might fail in capturing excessive credit growth after a boom-bust cycle. Figure 3 shows examples of this problem.

-The credit measure used in calculating the credit-to-GDP ratio is an aggregate and is not detailed enough to identify credit imbalances on a sectoral level. For example, the residential mortgage market grew excessively before the Great Recession leading to a system wide downfall. A more detailed approach would also allow policymakers to intervene more effectively.

-Lastly, the Hodrick-Prescott filtering technique used to obtain the long-term trend in credit is prone to measurement issues. The end-point of the sample strongly influences the trend, the size of the sample impacts the sign and size of the credit gap, and the choice of the length of the credit cycle required for calculating the filter is ambiguous.

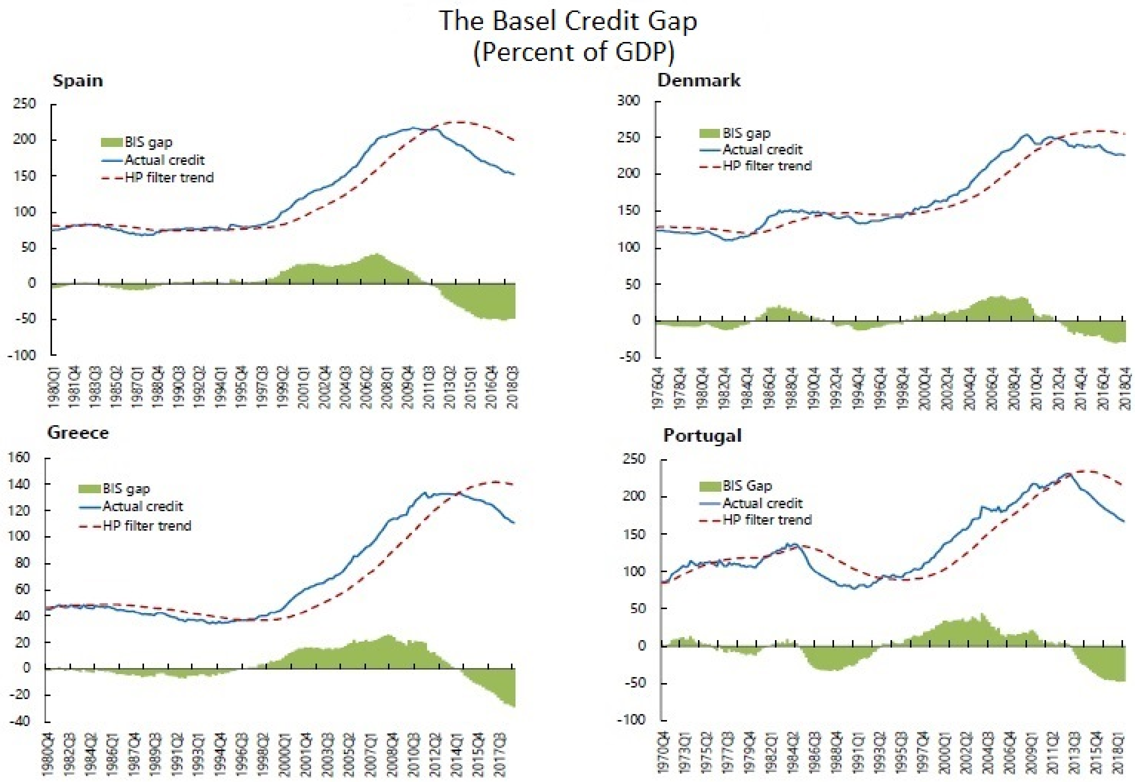


**Figure 3:** Basel III credit gap for four different countries. It also shows actual credit and the long-term trend using the Hodrick-Prescott filter. Source: Baba et al. (2020)

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# 3 Equilibrium credit

The notion of equilibrium credit as laid out by Buncic and Melecky (2014) is motivated by the quantity theory of money as for example described in Patinkin (1969) which states

$$MV = TP, \tag{1}$$

where M is the quantity of money, V the velocity of money, T is the volume of real transactions in the economy, and P is the price of these transactions. Buncic and Melecky (2014) alter this relation by substituting the quantity of money $M$ by the amount of credit $C$ given the growing importance of credit based transactions, resulting in

$$CV = TP. \tag{2}$$

In this case $C$ stands for the total amount of credit to the private sector. The relation in (2) can be approximated empirically using real GDP for $T$ and the GDP deflator for $P$. Buncic and Melecky (2014) then log-linearizes (2) and allow the price and income elasticity to differ from unity to get

$$c_t - (\beta^{gdp} gdp_t + \beta^{def} def_t) = -\nu_t, \tag{3}$$

where $c_t, gdp_t, def_t$, and $v_t$ are logarithmic transformations of credit to the private sector, real GDP, the GDP deflator, and credit velocity respectively. $\beta^{gdp}$ and $\beta^{def}$ represent the income and price elasticity of credit which Buncic and Melecky (2014) estimate to be unequal to unity. Equilibrium credit is then defined as $\beta^{gdp} gdp_t + \beta^{def} def_t$, which is interpreted as the transaction demand for credit of the real economy. Credit velocity is a disequilibrium measure that captures excess or lack of provided credit. Consequently, the credit gap of Buncic and Melecky (2014) is the difference between the amount of credit outstanding and this equilibrium.

The price and income elasticity parameters are estimated with an error-correction model assuming, based on (2), there is a long-run relation between nominal credit, real GDP, the GDP deflator, and credit velocity. This method belongs to the structural approach, where trends in credit are obtained with fundamental economic variables and the resulting residuals define the credit gap. Other examples of this approach can be found in Baba et al. (2020) and Lang and Welz (2019).

Because the goal is to find the effect between the credit gap and economic growth, where the latter is better represented in real terms than in nominal terms, I deviate from Buncic and Melecky (2014) and create a GDP based credit gap with real credit and real GDP, instead of using nominal credit and adding the GDP deflator. The construction of the credit gap based on real credit and real GDP is explained in Section 5.1. The next section provides an overview of the panel data set on real credit and real GDP. Importantly, it contains tests on unit roots and cointegration influencing the way the credit gap is made.

# 4 Data

## 4.1 Data description

I collect a sample of 36 countries to calculate the credit gap and investigate its relation with economic growth. The data is taken from the IMF's International Financial Statistics database and the Bank for International Settlements and is on a quarterly basis[2]. From the IMF database I use the real GDP and GDP deflator seasonally adjusted index series with base year 2010 (=100). From the Bank for International Settlements I use the "Credit to Private non-financial sector from All sectors at Market value - Adjusted for breaks" to represent the amount of credit outstanding in the economy. This is a raw data series, in nominal terms and not indexed. The adjustment for breaks is due to the broader coverage of borrowers, lenders and instruments nowadays used to calculate the total amount of credit[3]. All variables are in domestic currency.

## 4.2 Data adjustments

An initial inspection of the data reveals four cases where the observations make unusual changes. First, the Irish GDP indices and real credit index increase a lot from 2014Q4 to 2015Q1 (real credit goes up by 35%). Although this seems like an error, the explanation is that multinational companies moved their assets to Ireland due to its corporate tax rates, and given the relative size of these companies to Ireland the additional revenues suddenly made the Irish economy much bigger (OECD, 2016). Second, the real GDP and GDP deflator of Canada show strong movements from 1980Q4-1981Q1, where real GDP increases by approximately a factor 3.5 and the GDP deflator decreases by more or less the same factor. Canadian real credit does not exhibit the same changes. Because the same data on an annual frequency increase only gradually, I assume the change in the real GDP and GDP deflator series from 1980Q4-1981Q1 is incorrect and adjust the data such that it follows the same pattern as in the annual figures. This is done by making sure that the growth rate in the average of the quarterly data from 1980-1981 is equal to the growth rate in the annual data. All observations before 1980 can then be adjusted by backwards iteration using the quarterly growth rates of the original index series and the new index values obtained for 1980Q1-1980Q4.

The third and fourth case, of Japan from 1993Q4-1994Q1 and Mexico from 1992Q4-1993Q1, originates from the way quarterly nominal GDP is reported. Again comparing the quarterly IMF data with the annual data, annual nominal GDP is in some cases equal to the sum and in other cases equal to the average of the quarterly data. In case of Japan and Mexico, the reporting method changed in these periods from an average of quarters to the sum of quarters since 1994Q1 and 1993Q1 respectively. This caused the GDP deflator to drop to about a fourth from one quarter to the other. The real GDP and nominal credit series do not seem to be affected. Therefore, the GDP deflator is adjusted towards the most recent reporting standard using the same method applied to Canada by letting the growth rate in the averages of the quarterly data be equal to the growth rate in the annual data. This also keeps the base year 2010 with index

[2] See https://data.imf.org/?sk=4C514D48-B6BA-49ED-8AB9-52B0C1A0179B, "International Financial Statistics", and https://www.bis.org/statistics/totcredit.htm?m=6%7C380%7C669, "Credit to the non-financial sector", accessed: 04-06-2020.

[3] For details, see BIS (2013).

value 100 intact. After making these adjustments, the nominal credit series is first converted to a real credit series by dividing the credit series by the GDP deflator index series. Then, the real credit series is modified to an index series like real GDP and the GDP deflator because each countries scale and currency make the data analysis otherwise incomparable. This is done by dividing each observation by the average of the 2010 observations and multiplying by 100. Due to data availability, not every country has the same amount of observations. The range of the data is from 1952Q1 to 2019Q4 with the US having the most observations while Colombia has the fewest starting in 2005Q1. A list of all 36 countries in the data set and their observation range can be found in Appendix A.1.

### 4.3 Data summary

This section provides an overview of the data including the corrections made in Section 4.2, thus from now on I focus on real GDP and real credit. The data is log transformed to linearize the trend in the two variables and because the first difference after modification is approximately equal to the growth rate in the index series. Henceforth, the variable names represent the data in logs. Figure 4 shows the cross-country averages of the variables over time. As the base year is equal to 2010 for each variable, it should be no surprise that they intersect at that time. This also demonstrates that real credit has grown the faster, with an average growth rate of 1.15%, because it is below the real GDP variable before 2010 and above afterwards. The average growth rate of real GDP is 0.74%.

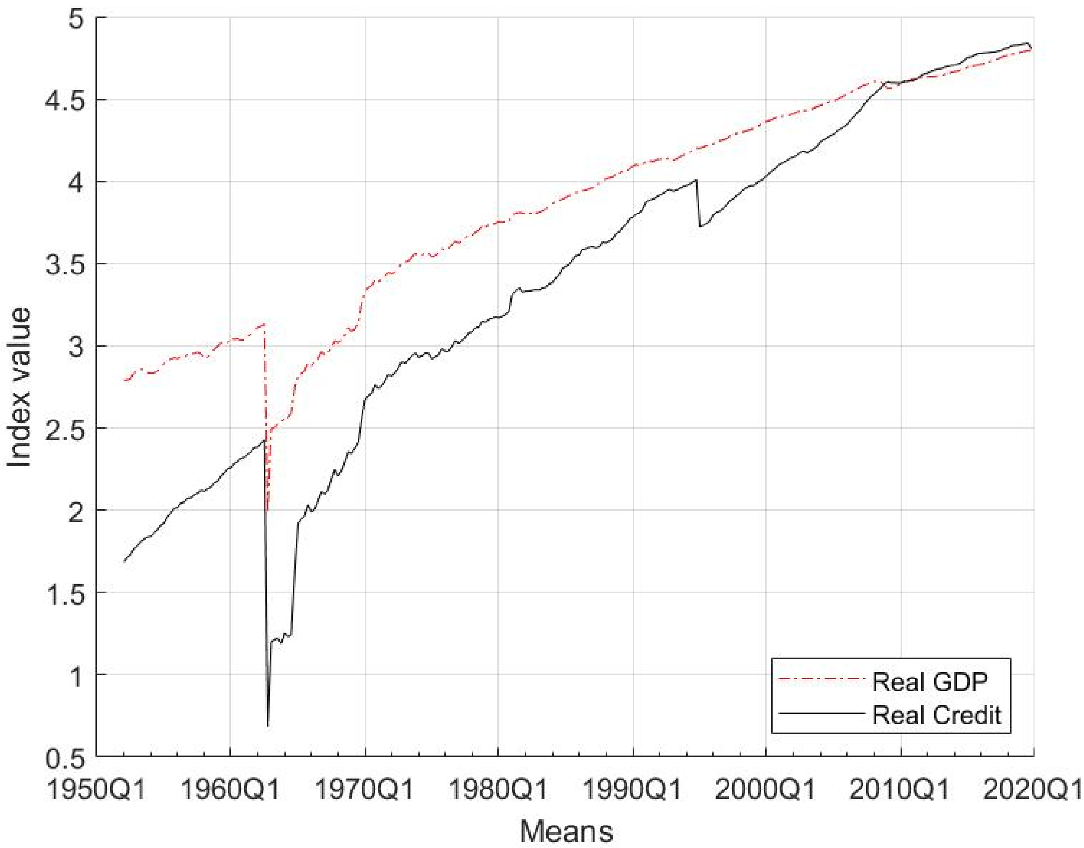


**Figure 4:** Time series of cross-country averages of real GDP and real credit.

The sudden jumps in the averages of the variables is explained by the unbalanced panel structure of the data set. The introduction of new countries to the data set leads to ambiguous changes to the variable averages. For example, before 1962Q4 the United States is the only country with data available, such that, when the new average is calculated including the faster growing Korea, the averages go down as Korea has lower index values at the time. In other cases, like the entry of Switzerland in 1970 and Canada in 1971 into the data, the averages go up.

Figure 5 gives the distribution of the first differences (growth rates) of real GDP and real credit at the country level. The mean and standard deviation are related across the two variables, i.e., countries with a lower mean real GDP growth also have a lower real credit growth and the same holds for the standard deviation. Some emerging economies like Mexico, Russia and Argentina have relatively volatile data. Besides, Figure 5 confirms that real credit has grown stronger on average than real GDP since the means are in almost any case higher in panel (b) than in panel (a). This implies that the credit-to-GDP ratio has been an increasing function over time which Buncic and Melecky (2014) relate to financial deepening and technological change.

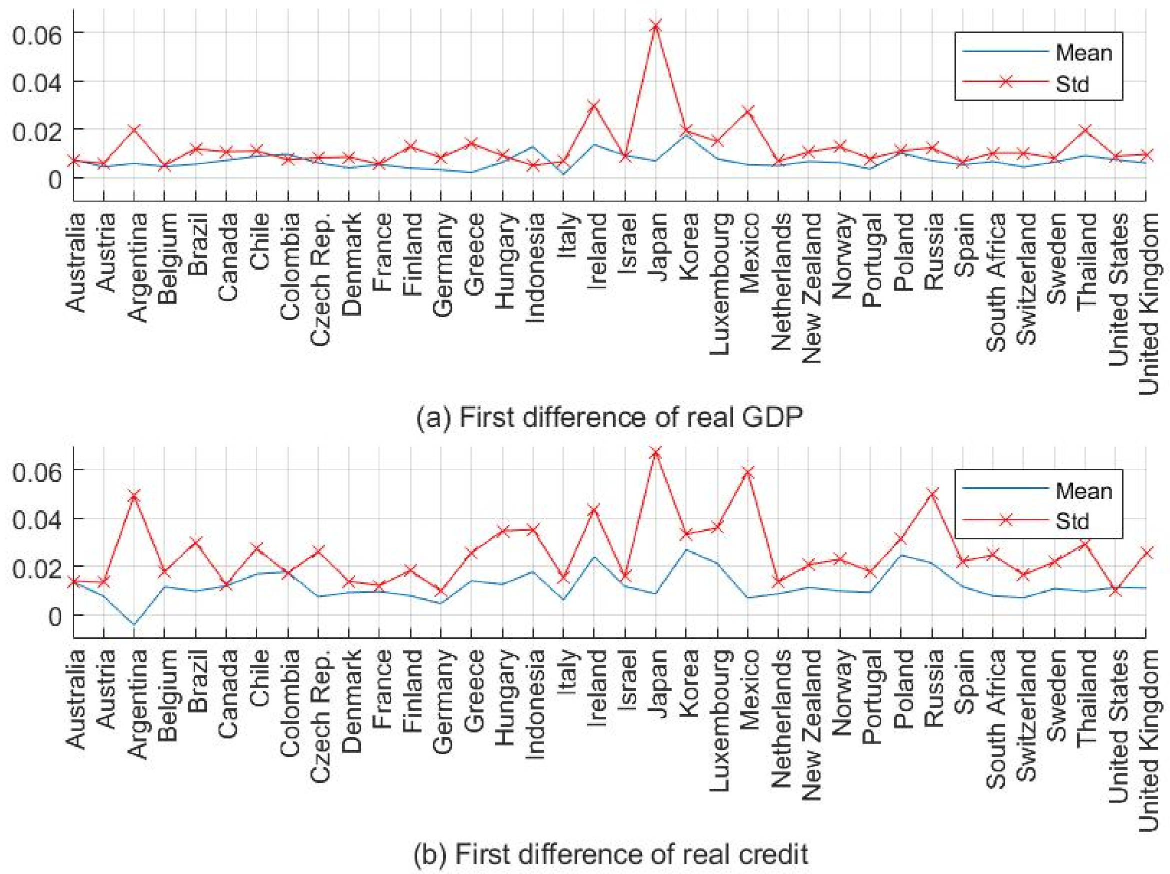


**Figure 5:** Mean and standard deviation (std) of the first differences per country. Panel (a) shows these statistics for real GDP, panel (b) plots them for real credit.

### 4.4 Outlier detection

The presence of outliers can potentially have a big impact on the results and thus the answer to the research question. Therefore, I investigate whether the data contains outliers. This is done in terms of the first differences of the four variables. Looking for outliers in the level data would automatically flag old or very recent observations because it is increasing over time. The mean or median of the data is somewhere in the middle of the time period such that any distance measure will regard these observations as outliers. It is thus better to consider the first differences which are more stable over time. Because the data is multivariate, examining outliers in a univariate way would ignore additional information about the observation. Consequently, I identify outliers with the Mahalanobis distance (Penny, 1996). Given a data set of size $n$ with $p$ variables, the Mahalanobis distance $D_i^2$ for each observation $i$ is equal to

$$D_i^2 = (x_i - \overline{x})' S^{-1} (x_i - \overline{x}), \tag{4}$$

where $\overline{x}$ is the vector of sample means and $S$ is the sample covariance matrix. Under the assumption that the data is multivariate normal, $D^2 \sim \frac{p(n-1)}{n-p} F_{p,n-p}$, where $F_{p,n-p}$ is the $F$-distribution with $p$ numerator degrees of freedom and $n-p$ denominator degrees of freedom (Penny, 1996). Hence, for a certain significance level $\alpha$, an observation is considered an outlier if $D_i^2$ is larger than the corresponding critical value of the $F$-distribution multiplied by $\frac{p(n-1)}{n-p}$.

Table I summarizes the distribution of the outliers on a country level. Using a 1% significance level, this procedure results in a total of 171 outliers. The six countries specifically shown are responsible for almost 75% of the outliers. The other outliers are spread over 17 different countries. Perhaps surprisingly, the outliers are not concentrated around economic crises but each country has its own time period in which the outliers occur. For example, the outliers of Korea and Japan appear early on in the data while Argentina's outliers are very recent, although the data on Argentina is more limited. To make sure that further results are not driven by the outliers, other results in this section will also be carried out excluding Japan, Mexico, Korea, Thailand, Argentina, and Russia.

**Table I**

**Distribution of outliers**

This table reports the distribution of outliers found in the first differences of the data on a country level. The outliers are detected by using the Mahalanobis distance at the 1% significance level.

| Country | Count | Cum. % |
|---|---|---|
| Japan | 43 | 25% |
| Mexico | 38 | 47% |
| Korea | 16 | 57% |
| Thailand | 10 | 63% |
| Argentina | 9 | 68% |
| Russia | 8 | 73% |
| Other | 47 | 100% |

### 4.5 Unit root and cointegration tests

Before modelling the relation between real credit and real GDP, statistical tests regarding the behavior of the data are conducted first. This means that unit root and cointegration tests are performed to assess whether the data is non-stationary and cointegrated. If the data is non-stationary it would have to be differenced to make it stable over time. In order to determine the appropriate tests regarding non-stationarity and cointegration, I first look at the cross-sectional dependence of the data. Cross-sectional dependence means that a certain variable moves together among different panels and can be weak, strong or absent depending on the magnitude of the co-movement (Pesaran, 2015). In case of strong cross-sectional dependence, unit root and cointegration tests which do not take this into account have low power (Pesaran, 2007). Weak cross-sectional dependence does not lead to significant estimation and inference problems given a reasonably large panel (Pesaran, 2015). I use the test of Pesaran (2004) to investigate the extent of the cross-sectional dependence. The null hypothesis of this test is weak cross-sectional dependence among the panels and the alternative is strong cross-sectional dependence. The test statistic is based on the pairwise correlations between residuals of different panels and is given by

$$CD = \sqrt{\frac{2}{N(N-1)}} \left( \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \sqrt{T_{ij}} \hat{\rho}_{ij} \right), \tag{5}$$

where $\hat{\rho}_{ij}$ is the estimated pairwise correlation between panel $i$ and $j$, $T_{ij}$ is the number of common observations and $N$ is the number of panels (Pesaran, 2004). The statistic follows the standard normal distribution under the null hypothesis. The residuals are obtained with an autoregressive (AR) model for the first differences for each country individually with 4 lags included. This model looks as follows

$$\Delta y_{it} = \alpha_i + \sum_{j=1}^{4} \beta_{ij} \Delta y_{i,t-j} + e_{it}, \tag{6}$$

where $y_{it}$ is the variable of interest (real GDP or real credit) of country $i$ at time $t$ and $e_{it}$ are the residuals used for the cross-sectional dependence test. The first differences are used because the subsequent unit root and cointegration tests are also performed with the first differences. The lag order is set to 4 to remove effects of serial correlation in these tests, and is determined by the persistence of the first differences based on the significant autocorrelations. These are mostly significant until the fourth lag. A similar persistence of order 3 is found in Chudik et al. (2017) for real GDP but real credit has stronger persistence. When choosing a lag order of 4, a majority of panels also satisfies the $4(T/100)^{2/9}$ rule of Newey and West (1994).

Table II reports the results of the cross-sectional dependence test. For both variables the null hypothesis of weak cross-sectional dependence is rejected which means that they have strong dependence cross-sectionally[4]. This result is robust to the outliers identified in Section 4.4. Hence, when testing for a unit root or cointegration, the presence of cross-sectional dependence has to considered.

[4]Similar results are obtained with 1 up to 8 lags.

**Table II**

## Cross-sectional dependence test

This table reports results of the cross-section dependence test. Column (1) reports the $CD$ test statistic for the AR(4) model including the six countries mentioned in Table I. Column (2) excludes them. $p$-values are reported in brackets where ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| | $CD$ | $CD$ |
|---|---|---|
| | (1) | (2) |
| Real GDP | 35.947*** | 32.452*** |
| | (0.000) | (0.000) |
| Real Credit | 7.758*** | 8.719*** |
| | (0.000) | (0.000) |
| No. countries | 36 | 30 |
| No. observations | 4454 | 3640 |

To test for a unit root I use the cross-sectionally augmented Dickey-Fuller (CADF) test which is based on a regression of the form

$$\Delta y_{it} = a_i + \gamma_i t + b_i y_{i,t-1} + c_i \overline{y}_{t-1} + \sum_{j=1}^{p} d_{ij} \Delta \overline{y}_{t-j} + \sum_{j=1}^{p} \delta_{ij} \Delta y_{i,t-j} + e_{it}, \tag{7}$$

where $p$ is the lag length to remove serial correlation (Pesaran, 2007). This unit root test is different from the standard ADF regression which does not include the $\overline{y}_{t-1}$ and $\Delta\overline{y}_{t-j}$ terms. These terms are added to account for cross-sectional dependence. As found in Table II, the strong cross-sectional dependence implies that other panel unit root tests of for example Choi (2001) or Im et al. (2003) cannot be applied. The null hypothesis of the CADF test is that $b_i = 0, \forall i$, and uses the least squares $t$-statistics of $b_i$ to assess this hypothesis. Because of the unbalanced panel data structure, the CADF test is performed using the normal approximation of the $t$-statistics. As shown in Pesaran (2007), the standardized version of these $t$-statistics is approximately standard normal, such that the statistic

$$Z_{tbar} = \frac{\sum_i^N (t_i - E(CADF_i))}{\sqrt{\sum_i^N Var(CADF_i)}}, \tag{8}$$

is also standard normal. Here, $t_i$ is the $t$-statistic in the CADF regression of country $i$, and $E(CADF_i)$ and $Var(CADF_i)$ are the mean and variance of the $t$-statistic. The unbalanced panel data causes the mean and variance of each $t$-statistic to be panel-specific, as the number of time series observations per country are different. Therefore, the usual CADF test which relies on a fixed time dimension for all panels is ruled out. The initial cross-sectional mean is subtracted from the data beforehand to ensure that the $t$-statistics do not depend on nuisance parameters and the $t$-statistics are truncated for the mean and variance to exist (Pesaran, 2007)[5].

[5]The normal approximation of the CADF test is implemented using Lewandowski (2006).

**Table III**

**Unit root test**

This table reports results of the unit root tests. Panel (A) provides results for the variables in levels. Panel (B) provides results in first differences. Column (1) implements the normal approximation of the CADF test including the six countries mentioned in Table I. Column (2) excludes them. The mean of the first time period is subtracted from the data. The lag length is set to 4. The reported statistic is $Z_{tbar}$. $p$-values are reported in brackets where ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Panel A: Levels | | |
|---|---|---|
| | $Z_{tbar}$ (1) | $Z_{tbar}$ (2) |
| Real GDP | 4.211 | 2.092 |
| | (1.000) | (0.982) |
| Real Credit | 2.199 | 1.233 |
| | (0.986) | (0.891) |
| Trend or constant included | Both | Both |
| No. countries | 36 | 30 |
| No. observations | 4454 | 3640 |
| **Panel B: First differences** | | |
| | $Z_{tbar}$ (1) | $Z_{tbar}$ (2) |
| Real GDP | $-14.646^{***}$ | $-13.803^{***}$ |
| | (0.000) | (0.000) |
| Real Credit | $-10.136^{***}$ | $-10.322^{***}$ |
| | (0.000) | (0.000) |
| Trend or constant included | Constant | Constant |
| No. countries | 36 | 30 |
| No. observations | 4418 | 3610 |

Table III reports the results of the test in levels and first differences. The lag length was for all panels set to 4 as argued earlier[6]. In case of the first differences, $\gamma_i$ in (7) is set to zero because the first differences are not trending. The null hypothesis of a unit root in all panels is not rejected for the levels but strongly rejected for the first differences. However, the alternative hypothesis of the CADF test is that some of the panels are stationary and thus not necessarily all. Also which panels are stationary is left unspecified. Regardless, the first differences will be treated as stationary as in for example, Buncic and Melecky (2014) and Chudik et al. (2017).

Now that the unit root in the levels of the variables has been established, I test for cointegration. Cointegration is the existence of a long-run relation between the variables, such that apart from short-run deviations the variables will always return to this long-run relation. In other words, cointegration means that a linear combination of the non-stationary variables is stationary. The presence of cointegration among the variables is tested using the methodology of Westerlund (2007). The method is based on the following equation

$$\Delta y_{it} = \delta_i' d_t + \alpha_i(y_{i,t-1} - \beta_i' x_{i,t-1}) + \sum_{j=1}^{p} \alpha_{ij} \Delta y_{i.t-j} + \sum_{j=-qi}^{p} \gamma_{ij} \Delta x_{i,t-j} + e_{it}, \tag{9}$$

[6]Similar results are obtained with 1 up to 8 lags.

where $d_t = (1,t)$ contains the constant and trend, $\alpha_i$ is the error correction parameter, and $q_i$ is the number of leads of the regressors to deal with exogeneity problems. Westerlund (2007) considers four tests where the null hypothesis of no cointegration, $\alpha_i = 0, \forall i$, is the same but the alternative is either that some $\alpha_i^{\prime}$s are nonzero in case of the group mean tests or that all $\alpha_i$ are nonzero in the panel tests. Both produce two statistics, $G_\tau$ and $G_\alpha$ for the mean group tests and $P_\tau$ and $P_\alpha$ for the panel tests. Their exact calculation can be found in Westerlund (2007). The strong cross-sectional dependence is accounted for by bootstrapping the distribution of the test statistics, which is nontrivial (Persyn & Westerlund, 2008). I test for cointegration between real GDP and real credit with real credit being the dependent variable.

Table IV presents the results of the cointegration test. With 4 lags, 2 leads and a Bartlett kernel width of 4, the null hypothesis of no cointegration is not rejected for both the panel and group mean tests[7]. The Westerlund test thus favors the nonexistence of a long-run relation between real credit and real GDP. This is in line with Buncic and Melecky (2014) who finds a unit root in the credit-to-GDP ratio (in logs) as credit has grown much faster than nominal GDP.

**Table IV**

**Cointegration test**

This table reports results of the cointegration test between real GDP and real credit. Column (1) implements the Westerlund test including the six countries mentioned in Table I. Column (2) excludes them. The lag length and width of the Bartlett kernel are set to 4, the lead length to 2. The trend and constant term are both included. The reported statistics are $G_\tau$ and $G_\alpha$ for the mean group tests and $P_\tau$ and $P_\alpha$ for the panel tests. The number of bootstraps is set to 800. $p$-values are reported in brackets where ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| | (1) | (2) |
|---|---|---|
| $G_\tau$ | −2.060 | −1.917 |
| | (0.889) | (0.961) |
| $G_\alpha$ | −8.668 | −7.585 |
| | (0.861) | (0.979) |
| $P_\tau$ | −13.202 | −9.578 |
| | (0.313) | (0.919) |
| $P_\alpha$ | −8.297 | −5.990 |
| | (0.249) | (0.920) |
| No. countries | 36 | 30 |
| No. observations | 4454 | 3640 |

# 5 Methodology

## 5.1 The GDP credit gap

The credit gap is a measure that indicates whether the current amount of credit provided is excessive or lacking. In Basel III it is the difference between the credit-to-GDP ratio and its long-run trend based on the Hodrick-Prescott filter and in Buncic and Melecky (2014) it is the difference between nominal credit and its equilibrium based on the sensitivity of nominal credit to real GDP and the GDP deflator (see Section 3). As mentioned earlier, the goal of this

[7]Increasing or decreasing the number of lags, leads or the width of the kernel by one or two, ceteris paribus, does not alter this finding.

paper is to estimate the effect of the credit gap, as a function of GDP, on economic growth (real GDP). Therefore, credit is also expressed in real terms which makes the role of the GDP deflator obsolete in calculating the credit gap. Because in Section 4.5 real GDP and real credit were shown to have a unit root without the existence of a cointegrating relation, a model relating the level of real credit to the level of real GDP could lead to a spurious regression. The slope parameter could be highly significant while in fact it is not. Therefore, I proceed by using the first differences of real credit and real GDP. The model takes the following form

$$\Delta c_{it} = \alpha_i + \sum_{j=0}^{p} \theta_{ij} \Delta gdp_{i,t-j} + \epsilon_{it}. \tag{10}$$

Here, $c_{it}$ and $gdp_{it}$ are the amount of real credit to the private sector and real GDP respectively, for country $i$ at time $t$, and $\alpha_i$ is the country specific constant. The lag order $p$ will be set to 4 as explained in Section 4.5. This model is estimated via least squares. The credit gap is then defined as the change in real credit unexplained by (10). Hence,

$$c_{it}^{gap} = \Delta c_{it} - \Delta \hat{c}_{it} = \epsilon_{it}. \tag{11}$$

By setting the credit gap equal to the residuals of (10) it has a mean of zero, such that a positive gap indicates excessive credit growth beyond what is required based on country-specific changes in real GDP. Using the residuals is in line with the structural approach relating credit to economic variables. However, other structural approaches have made use of a long-run relation between credit and its determinants, which seems absent between real credit and real GDP. The downside of not having a long-run relation is that the credit gap becomes very responsive to shocks in the determinants which makes capturing credit build-ups difficult. A solution is to find more variables until evidence of a long-run relation has been established.

### 5.2 Effect credit gap on economic growth

After the creation of the credit gap, the effect of the credit gap on economic growth is estimated. The effect is estimated using the common correlated effects mean group estimator (CCEMG) of Pesaran (2006). This estimator is used because of the cross-sectional dependence found in Section 4.5 and takes it into account by including cross-sectional averages of the dependent variable and the regressor in the regression. Simulation experiments of Pesaran (2006) show that the CCEMG estimator produces low bias for large panels with a multifactor error strcuture. The CCEMG model in this case takes the following form

$$\Delta gdp_{it} = c_i + \sum_{j=1}^{p} \lambda_{ij} \Delta gdp_{i,t-j} + \sum_{j=1}^{p} \beta_{ij} c_{i,t-j}^{gap} + \sum_{j=0}^{p} \zeta_{ij} \Delta \overline{gdp}_{t-j} + \sum_{j=1}^{p} \phi_{ij} \overline{c}_{t-j}^{gap} + u_{it}, \tag{12}$$

where $\Delta \overline{gdp}_t$ and $\overline{c}_t^{gap}$ are the cross-sectional averages of the first difference of real GDP and the credit gap respectively. After estimating (12) the panel-specific effects are averaged out to obtain the CCEMG estimates. Hence, this model allows for heterogeneous parameters among the countries. The assumption of a homogeneous effect of the gap on economic growth could be quite strong. For example, Chudik et al. (2017) argues that because of their degree of financial deepening, track record regarding debt obligations or political system, the effect of public debt on output growth could differ per country. The lag length $p$ is set to 4 given the persistence found in Section 4.5. However, with $p = 4$, the model has 18 parameters and can therefore not be regarded as a parsimonious model. Therefore, as a robustness check, (10) and (12) are also estimated with $p = 3$ and $p = 2$. Another issue with the regression of (12) is the fact that the credit gap is a generated regressor based on (10). How I deal with this issue is explained in Section 5.5.

### 5.3 Alternative credit gap: the BN decomposition

Because a long-run relation between real credit and real GDP is not found, extracting a trend from real credit using real GDP is not possible. Thus, as an alternative and given the current data set, I estimate a trend with only real credit itself. This trend component is obtained using the Beveridge-Nelson (BN) decomposition for real credit (Beverage & Nelson, 1981). The BN decomposition is able to split a unit root series into a cyclical and trend component. The use of the Beveridge Nelson decomposition is different from the regulatory Basel III approach in BCBS (2010) which uses the Hodrick-Prescott filter to derive estimates of the trend. This is because Hamilton (2018) shows that the Hodrick-Prescott filter introduces spurious dynamic relations and filtered values are very different at the end of the sample. The Beveridge-Nelson decomposition is calculated using the Kalman Filter, where the measurement equation for any given country reads

$$\Delta c_t - \mu = HX_t, \tag{13}$$

and state equation is given by

$$X_t = FX_{t-1} + \upsilon_t, \tag{14}$$

with $X_t$ being the state vector and $\upsilon_t \sim N(0, \Omega)$ the state disturbance term (Morley, 2002). Then the trend component can be computed as

$$\bar{c}_t = c_t + HF(I - F)^{-1}X_{t|t}, \tag{15}$$

where $X_{t|t}$ is the estimate of the state vector at time $t$. Consequently, the BN credit gap is the cyclical component such that

$$c_t^{BNgap} = -HF(I - F)^{-1}X_{t|t}. \tag{16}$$

The effect of this credit gap on economic growth is investigated using the same methodology of the GDP credit gap of Section 5.2. To keep things trivial in estimating the trend with the Kalman Filter I will only focus on AR models, with initially a lag order of 4. In that case, we have

$$H = \begin{pmatrix} 1 & 0 & 0 & 0 \end{pmatrix}, X_t = \begin{pmatrix} \Delta c_t - \mu \\ \Delta c_{t-1} - \mu \\ \Delta c_{t-2} - \mu \\ \Delta c_{t-3} - \mu \end{pmatrix}, F = \begin{pmatrix} \phi_1 & \phi_2 & \phi_3 & \phi_4 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}, \upsilon_t = \begin{pmatrix} \epsilon_t \\ 0 \\ 0 \\ 0 \end{pmatrix}. \tag{17}$$

The Kalman Filter is estimated with maximum likelihood where the log likelihood is equal to

$$L = -\frac{1}{2}\sum_{t=1}^{T} log|2\pi\Sigma_{t|t-1}| - \frac{1}{2}\sum_{t=1}^{T}(\Delta c_t - \mu - HX_{t|t-1})'\Sigma^{-1}_{t|t-1}(\Delta c_t - \mu - HX_{t|t-1}) \tag{18}$$

where $X_{t|t-1}$ is the time $t$ predicted state at time $t-1$ and $\Sigma_{t|t-1}$ is the predicted variance of $\Delta c_t$. For a detailed explanation of the Kalman Filter see the appendix of Elliott and Timmermann (2016).

### 5.4 Causality BN credit gap & economic growth

This section addresses the causal relation between the BN credit gap and economic growth. It is possible that changes in this gap affect growth or that growth causes changes in the gap. To this end, I perform a Granger causality test. A Granger causality test examines whether, for example, lags of the credit gap have any predictive power in explaining current economic growth after controlling for past values of economic growth. If they do, then the credit gap Granger causes economic growth. Note that a Granger causality test is not useful for the GDP credit gap of Section 5.1 because by definition past values of economic growth (changes in real GDP) cannot explain this gap. Causality can then only run one way, if present.

I test for Granger causality following the regression approach of Gelper and Croux (2007) which uses the forecast errors of a restricted and unrestricted model. This means in case of testing whether the BN credit gap Granger causes economic growth, that the unrestricted model is of the form

$$\Delta gdp_t = \omega + \sum_{k=1}^{p}\delta_k\Delta gdp_{t-k} + \sum_{k=1}^{p}\lambda_k c^{BNgap}_{t-k} + \eta_t. \tag{19}$$

Here $\omega$ is the constant, $\delta_k$ and $\lambda_K$ are coefficients of the $k$th lag, and $\eta_t$ is the error term[8]. The restricted model estimates (19) with $\lambda_k = 0, \forall k$. The forecast errors are based on the one-step ahead forecast series $\hat{y}_{R,t}$ and $\hat{y}_{U,t}$ for the restricted and unrestricted model respectively. According to Gelper and Croux (2007), there is no Granger causality if the forecast errors of the restricted model $u_{R,t} = y_t - \hat{y}_{R,t}$ have zero correlation with the difference between the forecast errors of both models $u_{R,t} - u_{U,t}$, with $u_{U,t} = y_t - \hat{y}_{U,t}$. This is evaluated by the regression

$$u_{R,t} = \xi(u_{R,t} - u_{U,t}) + e_t, \tag{20}$$

where in case of no Granger causality $\xi = 0$. In implementing the causality test, half of each country's observations is used to estimate (19) and the other half to calculate $\xi$. The lag length $p$ is again equal to 4. Although the standard method to evaluate this hypothesis is to do a likelihood ratio test, I will rely on the standard error of $\xi$ resulting from the bootstrapped data samples described in Section 5.5. This is because the credit gap is a generated regressor which adds uncertainty to the estimated parameters and forecast errors. This test of Granger causality will also be performed in the other direction with the credit gap as dependent variable

[8] $\delta_k$ and $\lambda_k$ are 36x36 matrices. To avoid blowing up the amount of parameters, these matrices are assumed to be diagonal such that there are no cross-country effects. Hence, (19) is estimated for each country separately.

and economic growth as the regressor.

### 5.5 Bootstrapping

The methodology as described in Section 5.2 and 5.4 make use of the credit gap. The credit gap is the result of either Section 5.1 or Section 5.3 such that further results are influenced by first-stage regression parameters or the Kalman Filter. Therefore, the standard errors in regressions using the credit gap are nontrivial. To solve this, I bootstrap the data using the nonparametric continuous moving block bootstrap algorithm of Phillips (2010), such that the standard error can be based on the bootstrapped distribution of the parameters. Consequently, for any parameter $a$ the standard error is equal to

$$SE_B(a) = \sqrt{\frac{1}{B-1}\sum_{r=1}^{B}\left(\hat{a}^r - \bar{a}^r\right)^2}, \tag{21}$$

where $\hat{a}^r$ is the parameter estimate of the $r$th bootstrap, $\bar{a}^r$ is their mean, and $B$ is the number of bootstraps (James et al., 2013). Assuming that the distribution of the bootstrap is normal, significance levels are obtained using the standard z-test.

The bootstrap algorithm is able to create new data samples and reflect the non-stationary character of the data as found in Section 4.5. The method relies on the temporal dependence usually contained in time series data by picking blocks of consecutive observations. In each new data set the first observation is based on the first observation of the original data. For the next observation a block of data is randomly selected to create differences which are then added to the first observation to generate new observations. This process is repeated until the new set of observations is the same size as the original. Consider a sample of length $n$, a block size $m$, let $N_1, ..., N_M$ be $i.i.d$ uniform draws from {1,2,...,$n-m$}, and let $M$=$[\frac{n}{m}]$ with $[\cdot]$ denoting the integer part (Phillips, 2010). Define $X_t$ as the matrix storing vectors of variables containing the observations at time $t$ for all countries such that its size is $i$x2 with $i$ being the number of countries. Then the first block of observations is equal to

$$X_k = X_1 + (X_{N_1+k} - X_{N_1}), \tag{22}$$

for $k$=1,...,m. Hence, after drawing the reference data point $X_{N_1}$, the $m$ subsequent observations are used to calculate differences with $X_{N_1}$, which are then added to $X_1$ to create the first $m$ bootstrapped observations. The succeeding blocks, with $s$=1,...,$M$-1, are then generated as

$$X_{sm+k} = X_{sm} + (X_{N_s+k} - X_{N_s}), \tag{23}$$

for $k$=1,...,m (Phillips, 2010). An advantage of the above algorithm is that all variables and countries are bootstrapped simultaneously keeping any dependencies between the countries and variables intact. However, the above algorithm is still a general description and is not completely suitable given the unbalanced data structure. This is because the matrix $X_t$ has empty elements when data of a particular country are not available. A couple of problems arise. First, a block could contain observations for countries which at that time did not yet have any data. The solution is to just remove the observations for these countries and only use the data for the relevant countries. Second, a similar problem arises when bootstrapping data near the end of the sample and a block of observations is picked earlier on such that the block has data on too few countries. This is solved by limiting the range of blocks that can be chosen to blocks containing observations of at least the number of required countries, the unnecessary ones can always be removed. For an overview of the data range per country, see Appendix A.1. In the data we have $n = 272$ and the block size $m$ is set to 4 because of the persistence of observations over time. I bootstrap 1000 data sets to estimate the standard errors when dealing with the GDP credit gap, and 250 when the analysis involves the BN credit gap. This is because of the computational burden of the Kalman Filter.

# 6 Results

## 6.1 Overview bootstrapped data

This section summarizes the bootstrapped time series of real GDP and real credit using the method explained in Section 5.5. Figure 6 shows the simulated data for a number of selected countries (Greece, Ireland, Mexico, and the US). For some countries in the data set, including Greece and the US, the bootstrapped data is usually below the original series. In other cases, like Ireland and Mexico, the original series is approximately in the middle of the simulated paths. Although the bootstrap technique is based on random sampling with replacement, which means that randomly selected observations can be used more than once to create one time series, the adjustments made to the continuous moving block bootstrap method cause the sampling to be not completely random. These adjustments, mentioned in Section 5.5, have been made to bootstrap from an unbalanced data set with cross-sectional dependence which restrict the available blocks to be selected for a certain time period. Consequently, the time period just before the Great Recession until the end of the sample seems to be overrepresented in the time series blocks used to construct simulated data sets. This is due to the small sample sizes of Colombia, Argentina, and Russia, only having data post 2004, 2003, and 2002, respectively. Sampling for these periods and onwards can only be done with data from that time period while sampling for earlier periods is sometimes also randomly based on that period, causing the overrepresentation. Given the fact that the Great Recession usually caused below average growth rates, the bootstrapped data sometimes ends up below the original time series, especially for countries with longer time series.

Figure 7 confirms the disproportionate influence of the most recent observations in creating the bootstrapped time series. It shows the total amount of times a certain reference data point $X_{N_M}$ (the observation used to calculate the differences with) was selected by the algorithm. The range of possible values is from 1 to 268 (n-m). Its distribution should be uniform if the data was balanced but is left-skewed due to the adjustments made to the bootstrapping algorithm. As a result of the overrepresentation of the most recent observations in the bootstrap, the bootstrapped data sets have a disproportionate tendency to follow them and therefore further results are biased towards the most recent trends in the data.

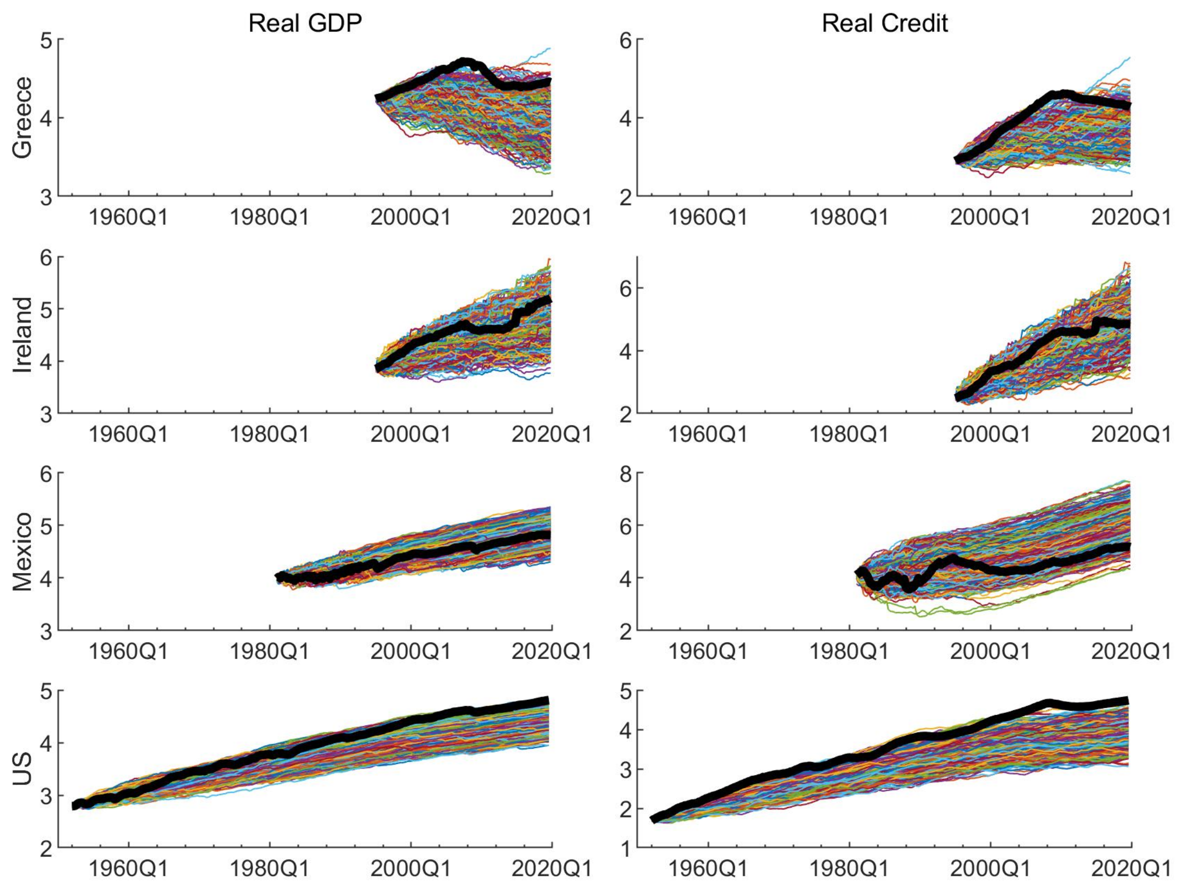


**Figure 6:** Examples of the original and bootstrapped time series of real GDP and real credit. The solid line indicates the original series, the thin lines the bootstrapped series.

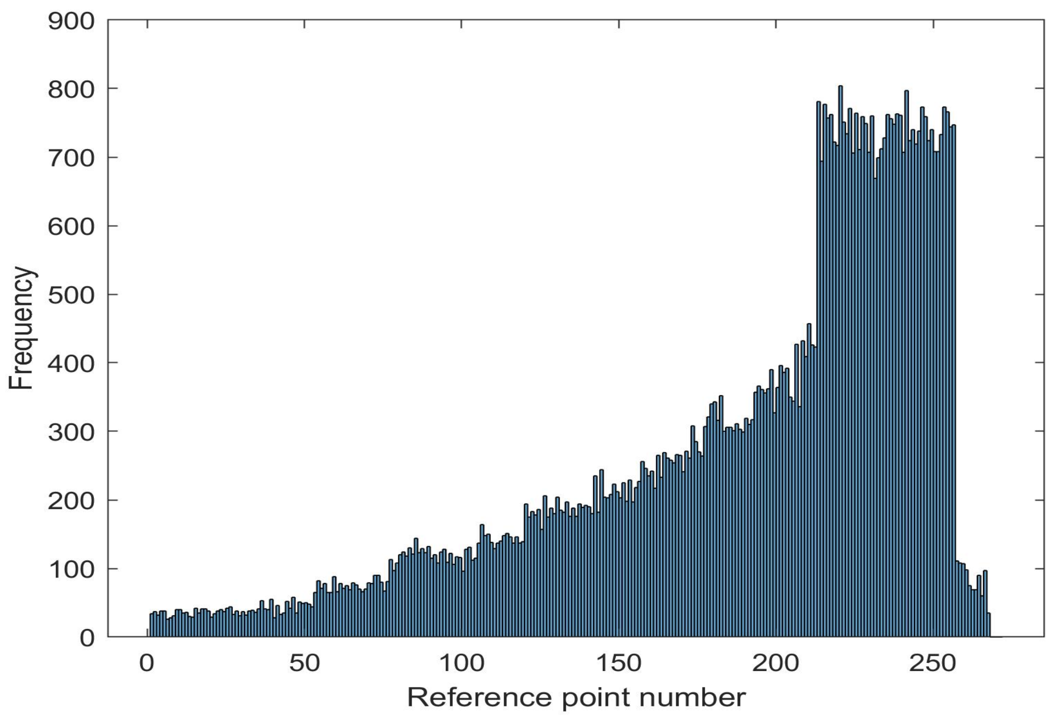


**Figure 7:** Distribution of reference points, $X_{N_M}$, used in the continuous block bootstrapping algorithm.

**Table V**

**Regressions of Real Credit on Real GDP, $p = 4$**

This table reports the results of regression (10) of changes in the first difference of real credit on changes in the first differences of real GDP with 4 lags included. The constant is included but not reported to conserve space. Statistical significance is based on the z-test with the bootstrapped standard error of Section 5.5. The standard error is also not reported. The number of bootstraps is set to 1000. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Country | $\Delta gdp_t$ (1) | $\Delta gdp_{t-1}$ (2) | $\Delta gdp_{t-2}$ (3) | $\Delta gdp_{t-3}$ (4) | $\Delta gdp_{t-4}$ (5) |
|---|---|---|---|---|---|
| Australia | 0.368* | 0.049 | 0.267 | 0.309 | 0.355* |
| Austria | 0.416** | 0.292* | 0.338* | −0.140 | 0.266 |
| Argentina | 0.266 | −0.581*** | 1.021*** | −0.181 | 0.199 |
| Belgium | 0.033 | −0.080 | 0.016 | 0.321 | 0.521 |
| Brazil | 0.101 | 0.598*** | 0.167 | 0.140 | 0.378* |
| Canada | 0.421 | −0.046 | 0.084 | 0.032 | 0.182* |
| Chile | −0.057 | −0.411 | 0.712** | 0.325 | 0.272 |
| Colombia | 0.887*** | 0.040 | 0.414 | 0.182 | 0.101 |
| Czech Republic | 0.525** | 0.112 | −0.560* | 0.492 | 0.302 |
| Denmark | 0.115 | 0.115 | 0.223 | −0.068 | 0.319* |
| France | 0.269** | 0.157 | −0.163 | 0.486*** | 0.061 |
| Finland | 0.078 | −0.129 | 0.175 | 0.174 | −0.132 |
| Germany | 0.070 | 0.017 | 0.067 | 0.043 | 0.004 |
| Greece | 0.452*** | 0.105 | −0.028 | 0.547*** | 0.368** |
| Hungary | −0.529 | −0.261 | 1.241*** | −0.344 | 0.579 |
| Indonesia | 0.296 | 2.419* | 3.202** | 0.638 | 0.229 |
| Italy | 1.163*** | −0.638*** | 0.304* | −0.147 | 0.627*** |
| Ireland | 0.823** | −0.007 | −0.183 | 0.044 | 0.154 |
| Israel | 0.483* | 0.185 | −0.056 | 0.013 | 0.286 |
| Japan | 0.765*** | 0.053 | −0.000 | 0.005 | 0.288*** |
| Korea | 0.426*** | 0.036 | 0.230* | 0.011 | 0.212** |
| Luxembourg | 0.587 | 0.321 | −0.018 | −0.010 | 0.478 |
| Mexico | 0.708** | −0.192 | 0.875*** | 0.674*** | −0.026 |
| Netherlands | 0.749*** | −0.456*** | 0.173 | −0.072 | 0.169 |
| New Zealand | 0.234 | 0.172 | 0.418** | −0.049 | 0.283 |
| Norway | 0.252* | 0.121 | 0.119 | 0.113 | 0.065 |
| Portugal | 0.283 | −0.159 | 0.220 | 0.419** | 0.661*** |
| Poland | 0.416* | −0.247 | 0.349 | 0.500 | 0.759*** |
| Russia | −0.539 | 0.790 | 0.206 | −0.134 | 1.635** |
| Spain | 0.965** | −0.378* | 0.751*** | 0.020 | 1.050*** |
| South Africa | 0.653*** | 0.129 | 0.248 | 0.263 | 0.288 |
| Switzerland | 0.271 | 0.006 | −0.025 | −0.089 | −0.044 |
| Sweden | −0.219 | 0.053 | −0.168 | −0.149 | 0.608** |
| Thailand | −0.008 | 0.271** | 0.149 | 0.069 | 0.252** |
| United States | 0.255*** | 0.331*** | 0.089 | 0.238*** | 0.155* |
| United Kingdom | 0.447** | 0.535** | −0.041 | 0.227 | 0.103 |

## 6.2 The GDP credit gap measure

The GDP based credit gap and its effect on economic growth are investigated next. Accordingly, Table V shows the coefficient estimates of equation (10), linking changes in real credit to contemporaneous and past changes in real GDP, when $p = 4$. There is a lot of variation in the size and significance of the coefficients of changes in real GDP. In some cases real credit does not respond to real GDP at all, or only after a few quarters, but the effect is usually significant in the contemporaneous period or the 4th lag. For interpretation, take UK's coefficient 0.447 of change in real GDP at time t, it means that a 1% increase in real GDP leads to a 0.45%

increase in real credit in the same period. Appendix A.2 gives the results for $p = 3$ and $p = 2$. Lowering the number of lags allowed in the regression changes both the size and significance of the coefficients. The GDP credit gap is thus sensitive to the choice of $p$. At this stage, concerns about serial correlation, heteroskedasticity and cross-sectional dependence in the residuals are not an issue because they are characteristics of the GDP credit gap measure, which is defined as the residuals of (10). By bootstrapping, the standard errors of Table V should be robust to serial correlation and heteroskedasticity and cross-sectional dependence will be taken into account when estimating the effect of the GDP credit gap on real GDP. The goal is only to obtain a credit gap that captures credit growth unexplained by GDP.

Figure 8 plots the GDP credit gap, real credit and its implied trend, obtained by adding the fitted real credit growth to the previous real credit value, for 4 different countries. The gap by definition moves around zero but does so in a very volatile way. Moreover, the gaps are quite small such that real credit and its trend are almost identical. Compared to the regulatory credit gap of Figure 3, there are no clear prolonged periods in which the GDP credit gap is positive signaling the build-up of excessive credit. This is most likely due to the first differences of real credit which behave as a stationary series around zero similar to the residuals. Structural approaches fitting a trend in the level of credit are more easily able to generate highly persistent residuals being either positive or negative for a prolonged period of time, as shown in Baba et al. (2020).

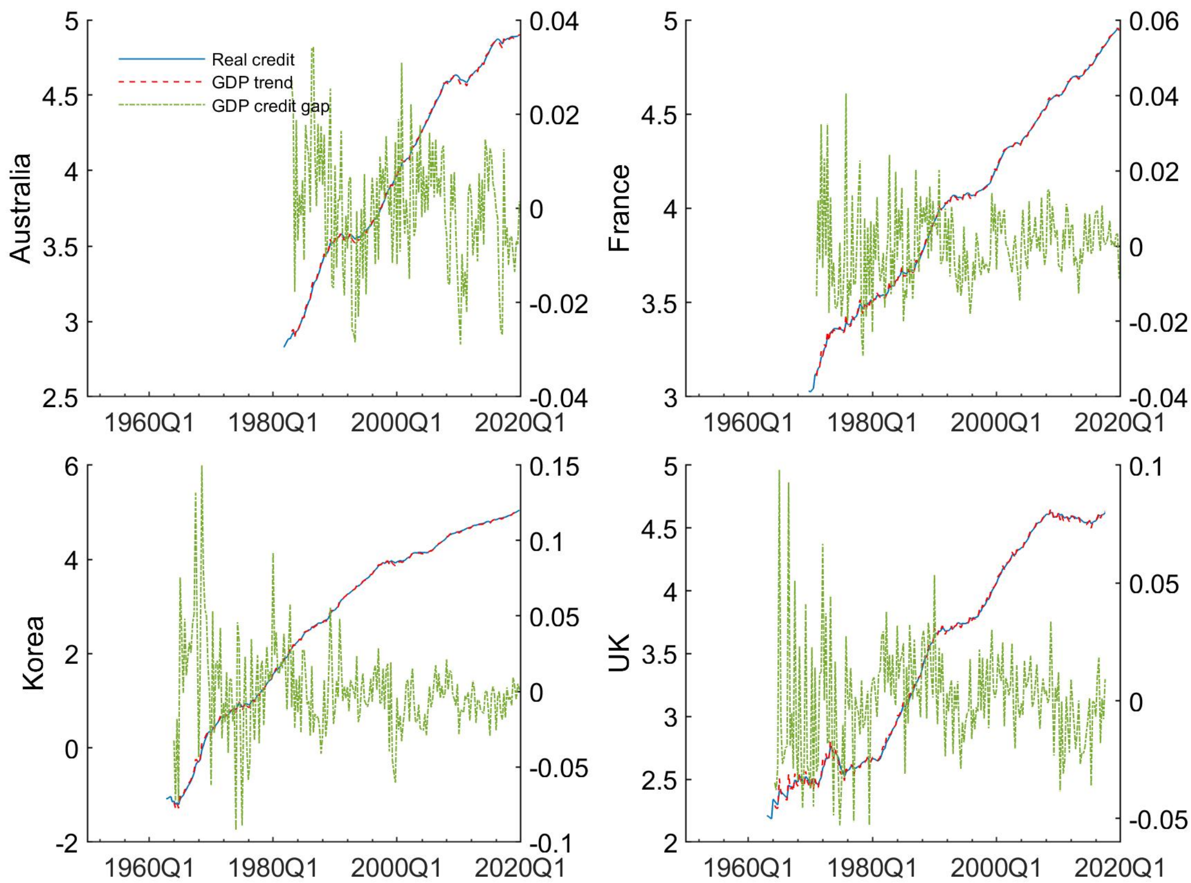


**Figure 8:** Time series of real credit, the GDP credit gap (right axis) and the implied trend with $p = 4$. The blue solid line indicates real credit, the red dashed line the trend, and the green dash-dotted line the GDP credit gap.

**Table VI**

## Regressions of Real GDP on GDP Credit Gap

This table reports the results of regression (12) of the first difference of real GDP on the GDP credit gap, their lags and (lags of) their cross-sectional averages. The bootstrapped standard error is given in parenthesis using the bootstrap method of Section 5.5. The number of bootstraps is set to 1000. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| | $p = 4$ | $p = 3$ | $p = 2$ |
|---|---|---|---|
| Constant | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) |
| $\Delta gdp_{t-1}$ | −0.001 | 0.000 | 0.036 |
| | (0.034) | (0.033) | (0.032) |
| $\Delta gdp_{t-2}$ | 0.089*** | 0.070*** | 0.106*** |
| | (0.028) | (0.027) | (0.026) |
| $\Delta gdp_{t-3}$ | 0.057** | 0.031 | |
| | (0.029) | (0.027) | |
| $\Delta gdp_{t-4}$ | 0.011 | | |
| | (0.029) | | |
| $c^{gap}_{t-1}$ | 0.011 | 0.015 | 0.011 |
| | (0.011) | (0.011) | (0.010) |
| $c^{gap}_{t-2}$ | 0.001 | 0.001 | −0.003 |
| | (0.011) | (0.011) | (0.010) |
| $c^{gap}_{t-3}$ | −0.011 | −0.003 | |
| | (0.011) | (0.011) | |
| $c^{gap}_{t-4}$ | −0.006 | | |
| | (0.012) | | |
| $\Delta\overline{gdp}_t$ | 0.989*** | 0.975*** | 1.035*** |
| | (0.031) | (0.028) | (0.025) |
| $\Delta\overline{gdp}_{t-1}$ | 0.022 | 0.048 | −0.009 |
| | (0.045) | (0.042) | (0.040) |
| $\Delta\overline{gdp}_{t-2}$ | −0.107*** | −0.118*** | −0.112*** |
| | (0.040) | (0.038) | (0.035) |
| $\Delta\overline{gdp}_{t-3}$ | −0.032 | 0.017 | |
| | (0.043) | (0.039) | |
| $\Delta\overline{gdp}_{t-4}$ | −0.024 | | |
| | (0.042) | | |
| $\bar{c}^{gap}_{t-1}$ | −0.053** | −0.036* | −0.030 |
| | (0.023) | (0.021) | (0.019) |
| $\bar{c}^{gap}_{t-2}$ | 0.029 | 0.008 | 0.016 |
| | (0.022) | (0.021) | (0.018) |
| $\bar{c}^{gap}_{t-3}$ | −0.015 | −0.007 | |
| | (0.022) | (0.020) | |
| $\bar{c}^{gap}_{t-4}$ | 0.026 | | |
| | (0.022) | | |
| No. countries | 36 | 36 | 36 |
| No. observations | 4310 | 4382 | 4454 |
| Adj. $R^2$ | 0.405 | 0.373 | 0.349 |

Table VI shows the results of equation (12), which tries to estimate the effect of the GDP credit gap on future economic growth (changes in real GDP), for different values of $p$. It reports the mean group estimates such that the reported coefficients are the average effects for all countries. With the bootstrapped standard errors, the coefficients of $c^{gap}_t$ are not significantly different from zero. Only some past changes in real GDP and cross-sectional averages are significant. This holds for $p = \{2, 3, 4\}$. Hence, changes in real credit, not explained by changes in real GDP, do not have any effect on future changes in real GDP. The GDP credit gap is not a good instrument in determining credit provision because it lacks a relation with real GDP.

**Table VII**

**Results BN decomposition of Real Credit, $p = 4$**

This table reports the results of the Beveridge-Nelson (BN) decomposition of real credit with 4 lags included. The decomposition is estimated with the Kalman Filter using (13) as measurement equation and (14) as state equation. Statistical significance is based on the z-test with the bootstrapped standard error of Section 5.5. The standard error is not reported to conserve space. The number of bootstraps is set to 250. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Country | $\mu$ (1) | $\phi_1$ (2) | $\phi_2$ (3) | $\phi_3$ (4) | $\phi_4$ (5) |
|---|---|---|---|---|---|
| Australia | 0.014*** | 0.249*** | 0.264*** | 0.008 | 0.000 |
| Austria | 0.007*** | 0.098 | −0.000 | 0.000 | 0.000 |
| Argentina | −0.004 | −0.167 | 0.000 | −0.000 | −0.000 |
| Belgium | 0.012*** | 0.106 | 0.286*** | −0.004 | 0.000 |
| Brazil | 0.011*** | 0.103 | 0.000 | 0.000 | −0.000 |
| Canada | 0.012*** | 0.185*** | 0.172*** | 0.004 | 0.000 |
| Chile | 0.016*** | 0.324*** | −0.000 | −0.000 | −0.000 |
| Colombia | 0.018* | 0.179 | 0.314*** | 0.008*** | 0.000 |
| Czech Republic | 0.006** | 0.159 | −0.000 | −0.000 | 0.000 |
| Denmark | 0.009* | 0.192 | 0.217*** | 0.004 | 0.000 |
| France | 0.009 | 0.079 | 0.182*** | −0.082 | 0.373*** |
| Finland | 0.007*** | 0.368*** | 0.000 | 0.000 | −0.000 |
| Germany | 0.004 | 0.126 | 0.157** | 0.007 | 0.320*** |
| Greece | 0.010** | 0.182** | 0.274** | 0.339*** | 0.011*** |
| Hungary | 0.014*** | 0.002 | 0.163** | −0.007*** | 0.000 |
| Indonesia | 0.017*** | 0.009 | 0.000 | −0.000 | 0.000 |
| Italy | 0.006*** | 0.046 | 0.370*** | 0.017 | 0.341*** |
| Ireland | 0.024*** | 0.148 | 0.000 | 0.000 | 0.000 |
| Israel | 0.011*** | 0.038 | 0.276*** | −0.008*** | 0.000 |
| Japan | 0.007*** | −0.054 | −0.058 | −0.038 | 0.856*** |
| Korea | 0.029*** | 0.145* | 0.152** | 0.065 | 0.262*** |
| Luxembourg | 0.021*** | 0.630*** | 0.000 | −0.000 | −0.000 |
| Mexico | 0.005 | 0.071 | 0.227*** | −0.065 | 0.248*** |
| Netherlands | 0.008*** | 0.051 | 0.194*** | −0.009 | 0.000 |
| New Zealand | 0.011*** | 0.061 | −0.000 | −0.000 | 0.000 |
| Norway | 0.010*** | 0.285*** | 0.000 | −0.000 | −0.000 |
| Portugal | 0.005*** | 0.324*** | 0.243*** | 0.264*** | −0.014*** |
| Poland | 0.024*** | 0.376*** | 0.000 | 0.000 | −0.000 |
| Russia | 0.021** | 0.159 | −0.000 | 0.000 | 0.000 |
| Spain | 0.011*** | 0.359*** | 0.112** | 0.133*** | 0.313*** |
| South Africa | 0.008*** | 0.173** | 0.103* | 0.006 | 0.000 |
| Switzerland | 0.007*** | −0.015 | 0.117* | −0.086*** | 0.191*** |
| Sweden | 0.011* | 0.120 | 0.000 | 0.000 | 0.000 |
| Thailand | 0.008*** | 0.152 | 0.365*** | 0.014 | 0.000 |
| United States | 0.010*** | 0.212*** | 0.414*** | −0.117*** | 0.338*** |
| United Kingdom | 0.010 | 0.025 | 0.068 | 0.116*** | 0.260*** |

### 6.3 The BN credit gap

Now that the effect of the GDP credit gap has been deemed insignificant, this section investigates the usefulness of the alternative BN credit gap using the Beveridge-Nelson decomposition. In order to create this credit gap, Table VII reports the Kalman Filter estimates of equations (13) and (14) with $p = 4$. These state space equations represent an AR model for the first difference of real credit. Hence, the $\mu$ can be interpreted as the estimated mean real credit growth rate and the $\phi$'s as the autoregressive parameters. Unlike the first lag of the first difference of real credit, most coefficients are set close to zero at higher orders. This means that these are not useful to predict future real credit growth since the Kalman Filter minimizes the prediction error. Like the construction of the GDP credit gap, there is a lot of variation in the size and significance of the coefficients between countries. Compared to the results with $p = 3$ or $p = 2$, which can be found in Appendix A.3, the coefficients do not change much if the omitted lag orders are insignificant, but do have an impact if they are significant, suggesting the specifications with lower $p$ leave out important dynamics.

Figure 9 shows the BN credit gap, the corresponding trend and real credit for the same countries as in Figure 8. In contrast to the GDP credit gap, the BN credit gap is less volatile and has periods in which the gap stays either negative or positive for several quarters in a row. However, the Basel credit gap of Figure 3 still has more persistence with episodes lasting more than a business cycle. Interestingly, prior to the Financial Crisis the BN credit gap was either decreasing and/or negative which is at odds with the idea that credit growth was excessive in that period. This could be because the BN credit gap, defined by a short AR process, adjusts relatively quick to the most recent growth rates.

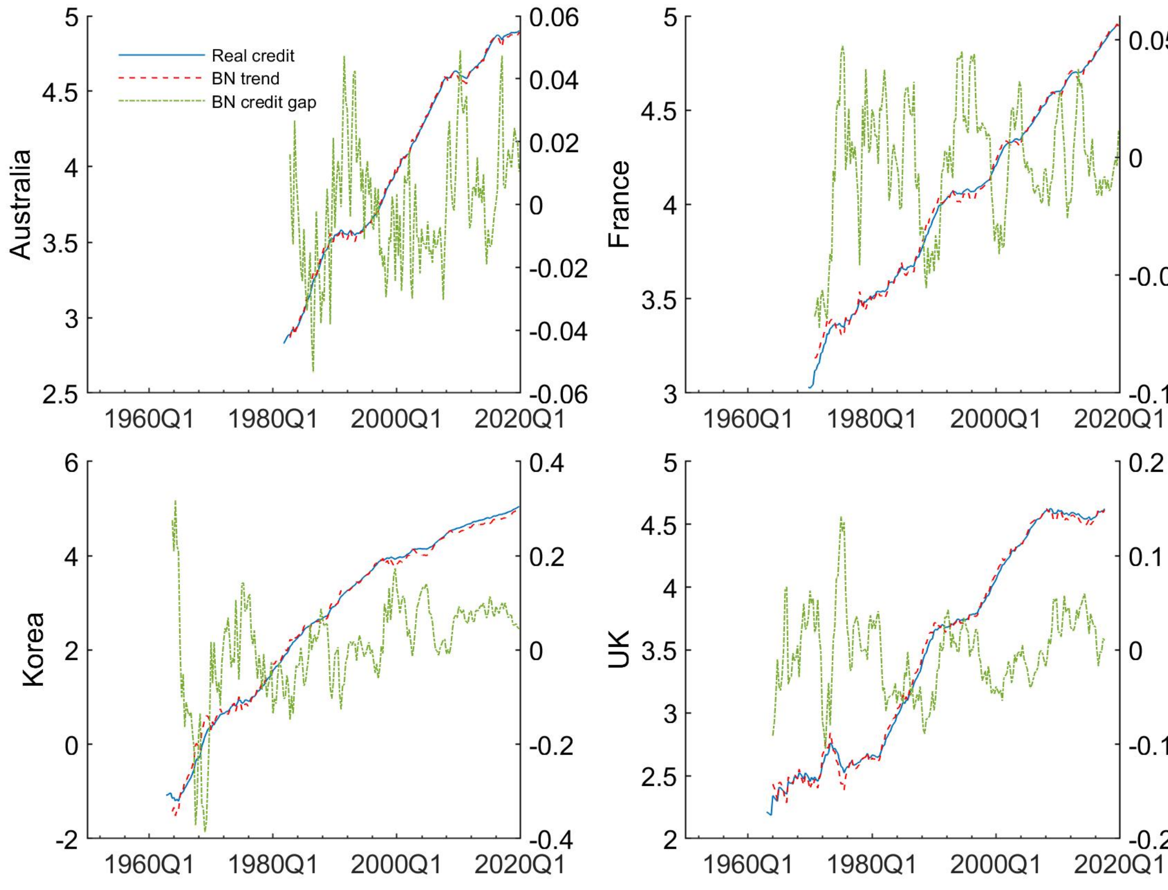


**Figure 9:** Time series of real credit and the trend using the Beveridge-Nelson decomposition with $p = 4$ (left axis), and the resulting BN credit gap (right axis). The blue solid line indicates real credit, the red dashed line the trend, and the green dash-dotted line the BN credit gap.

**Table VIII**

## Regressions of Real GDP on BN Credit Gap

This table reports the results of regression (12) of the first difference of real GDP on the BN credit gap, their lags and (lags of) their cross-sectional averages. The bootstrapped standard error is given in parenthesis using the bootstrap method of Section 5.5. The number of bootstraps is set to 250. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| | $p = 4$ | $p = 3$ | $p = 2$ |
|---|---|---|---|
| Constant | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) |
| $\Delta gdp_{t-1}$ | $-0.015$ | 0.005 | 0.001 |
| | (0.033) | (0.032) | (0.030) |
| $\Delta gdp_{t-2}$ | 0.070** | 0.081*** | 0.096*** |
| | (0.027) | (0.026) | (0.025) |
| $\Delta gdp_{t-3}$ | 0.031 | 0.012 | |
| | (0.031) | (0.029) | |
| $\Delta gdp_{t-4}$ | 0.007 | | |
| | (0.032) | | |
| $c_{t-1}^{BNgap}$ | $-0.098$ | $-0.140$ | $-0.085$ |
| | (4.894) | (4.149) | (3.585) |
| $c_{t-2}^{BNgap}$ | $-0.106$ | $-0.144$ | $-0.196$ |
| | (3.798) | (3.419) | (2.138) |
| $c_{t-3}^{BNgap}$ | 0.036 | 0.127 | |
| | (3.905) | (3.769) | |
| $c_{t-4}^{BNgap}$ | 0.043 | | |
| | (2.167) | | |
| $\Delta \overline{gdp}_t$ | 1.007*** | 0.985*** | 1.017*** |
| | (0.032) | (0.029) | (0.028) |
| $\Delta \overline{gdp}_{t-1}$ | 0.057 | 0.039 | 0.031 |
| | (0.046) | (0.043) | (0.042) |
| $\Delta \overline{gdp}_{t-2}$ | $-0.095$** | $-0.108$*** | $-0.092$*** |
| | (0.038) | (0.035) | (0.033) |
| $\Delta \overline{gdp}_{t-3}$ | $-0.014$ | 0.013 | |
| | (0.041) | (0.039) | |
| $\Delta \overline{gdp}_{t-4}$ | $-0.002$ | | |
| | (0.045) | | |
| $\bar{c}_{t-1}^{gap}$ | 0.035 | 0.027 | $-0.001$ |
| | (0.058) | (0.052) | (0.050) |
| $\bar{c}_{t-2}^{gap}$ | $-0.029$ | 0.007 | 0.024 |
| | (0.059) | (0.056) | (0.047) |
| $\bar{c}_{t-3}^{gap}$ | 0.039 | $-0.017$ | |
| | (0.055) | (0.045) | |
| $\bar{c}_{t-4}^{gap}$ | $-0.046$ | | |
| | (0.050) | | |
| No. countries | 36 | 36 | 36 |
| No. observations | 4346 | 4418 | 4490 |
| Adj. $R^2$ | 0.402 | 0.374 | 0.354 |

To determine whether the BN credit gap has an effect on economic growth, Table VIII presents the results of equation (12) and shows the mean group estimates of regressing the first difference of real GDP on the BN credit gap. Similar to Table VI, the effect of the credit gap is insignificant. The only significant coefficients are past changes in real GDP and some cross-sectional averages of real GDP changes. Notice the standard errors of the BN credit gap coefficients are very large. This is because the block bootstrap algorithm sometimes generates relatively random credit series for a certain country. As a consequence, its $\phi_1$ becomes very close to zero such that the resulting BN credit gap is very small as well. To compensate for the small gap, the coefficient can be as much as a 100 or even 1000 times larger than its usual size and thus affects the mean group estimate and the standard error of the mean group coefficient distribution. On the other hand, even after removing the 1% most extreme coefficients of the BN credit gap in the bootstrap, the coefficients would still be insignificant[9]. Therefore, the BN credit gap, like the GDP credit gap, seems to have no effect on real GDP.

The absent effect of the BN credit gap on real GDP is further substantiated by the results of the Granger causality test. Table IX reports $\xi$ of equation (21) which measures whether the unrestricted model improves the prediction of the dependent variable over the restricted model. This means that, in case of testing if the BN credit gap Granger causes real GDP, adding the BN credit gap to the regressors improves the prediction of real GDP. According to Panel A this is not true. The null hypothesis of $\xi = 0$ cannot be rejected for all $p$. On the other hand, there is evidence that real GDP Granger causes the BN credit gap. For $p = 4$ and $p = 2$, $\xi$ is not equal to zero. Therefore, Granger causality runs from real GDP to the BN credit gap and not the other way around.

**Table IX**

**Granger Causality test**

This table reports results of the Granger causality tests. Panel (A) tests Granger causality of the BN credit gap on real GDP. Panel (B) tests Granger causality of real GDP on the BN credit gap. Column (1) shows the results when $p = 4$, Column (2) when $p = 3$, and Column (3) when $p = 2$. The reported statistic is $\xi$. The bootstrapped standard error is given in parenthesis using the bootstrap method of Section 5.5. The number of bootstraps is set to 250. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| | Panel A: BN credit gap | | |
|---|---|---|---|
| | $p = 4$ | $p = 3$ | $p = 2$ |
| | (1) | (2) | (3) |
| $\xi$ | 0.055 | 0.003 | 0.007 |
| | (0.245) | (0.982) | (0.046) |
| No. countries | 36 | 36 | 36 |
| No. observations | 2287 | 2287 | 2287 |
| | **Panel B: Real GDP** | | |
| | $p = 4$ | $p = 3$ | $p = 2$ |
| | (1) | (2) | (3) |
| $\xi$ | $-1.655^{***}$ | $-0.597$ | $-0.382^{***}$ |
| | (0.605) | (0.404) | (0.054) |
| No. countries | 36 | 36 | 36 |
| No. observations | 2287 | 2287 | 2287 |

# 7 Conclusion

This paper has investigated the effect of two different credit gaps on economic growth, where the latter is represented by the first difference in real GDP. The first credit gap is initially based on the idea of equilibrium credit, which assumes a long-run relation between the levels of credit and GDP. However, no long-run relation is found between real credit and real GDP when controlling

[9]Removing the most extreme 1% results in standard errors of 0.291 and 0.193 for $c_t^{BNgap}$ when $p = 2$. For larger $p$ the changes are similar.

for cross-sectional dependence. The GDP credit gap is therefore defined as real credit growth unexplained by short-run changes in real GDP. Based on an unbalanced panel of 36 countries, the effect of the GDP credit gap is insignificant.

As an alternative to the GDP credit gap, the Beveridge-Nelson is used to divide the real credit series in a trend and cycle component. These two components are obtained with an autoregressive state space model for the first difference of real credit, which is estimated using the Kalman Filter. The BN credit gap is then defined as the obtained cycle component. This credit gap is more persistent than the GDP credit gap with longer periods being either positive or negative but still more volatile than the regulatory Basel credit gap. Similar to the GDP credit gap, the effect of the BN credit gap on economic growth is also insignificant. The BN credit gap has additionally been tested for Granger causing real GDP by determining whether the BN credit gap improves forecasting real GDP out-of-sample over a fully autoregressive model. However, the BN credit gap did not provide a significant improvement whereas adding real GDP to a forecasting model for the BN credit gap did lead to better models. Causality thus seems to run in the other direction which makes the BN credit gap as an instrument in determining credit provision more troublesome.

Several contributions have been made to the existing literature. First, two new credit gaps have been used, though their practical use is questionable. Second, the data covers a large panel of 36 countries with more than 4500 observations. Third, throughout the paper the presence of cross-sectional dependence has been taken into account. Not only in the unit root tests and cointegration test, but also in the bootstrap algorithm and when estimating the effect of the gaps on economic growth by using the common correlated effects mean group estimator. Finally, the nonparametric continuous block bootstrap has been adjusted to be able to simulate unbalanced panel data sets. This is done by restricting the available blocks to be selected by the algorithm when time passes.

The applied methodology also has a few shortcomings. Conceptually, the GDP credit gap is only based on the relation of real credit with real GDP which would imply it is the single determinant of real credit. Other structural approaches have used more than one determinant with the additional advantage of the existence of a long-run relation between them which makes more sense when looking for a good method to find the right amount of credit. Another shortcoming is in the bootstrap method, which is not completely random due to the imposed restrictions. Consequently, the simulated data does not behave completely like the original data especially for countries with a longer time series. This may cast doubt on the estimated standard errors and the significance of the coefficients. The standard errors of the effect of the BN credit gap are affected in particular. A solution might be to use a parametric bootstrap method such that the data is assumed to behave according to a specific model but this raises the issue of model uncertainty. Hence, a trade-off exists.

Further research in the area of credit provision can extend the structural and statistical approaches by using more variables and different methods. In addition, other aspects of credit gaps than their effect on economic growth are also worth investigating. For example, to forecast credit or economic crashes, to determine when buffers should be released, or the effect of credit gaps on other economic variables.

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# A Appendix

## A.1 Data Set

**Table X**
**Data Overview**

| Country | Sample size (1) | No. observations (2) |
|---|---|---|
| Australia | 1981Q4 - 2019Q4 | 153 |
| Austria | 1996Q1 - 2019Q4 | 96 |
| Argentina | 2004Q1 - 2019Q4 | 64 |
| Belgium | 1995Q1 - 2019Q4 | 100 |
| Brazil | 1996Q4 - 2019Q3 | 95 |
| Canada | 1971Q1 - 2019Q2 | 194 |
| Chile | 1996Q1 - 2019Q4 | 96 |
| Colombia | 2005Q1 - 2019Q3 | 59 |
| Czech Republic | 1996Q1 - 2019Q4 | 96 |
| Denmark | 1995Q1 - 2019Q4 | 100 |
| France | 1969Q4 - 2019Q4 | 201 |
| Finland | 1990Q1 - 2019Q4 | 120 |
| Germany | 1991Q1 - 2019Q4 | 116 |
| Greece | 1995Q1 - 2019Q4 | 100 |
| Hungary | 1995Q1 - 2019Q4 | 100 |
| Indonesia | 2000Q1 - 2019Q4 | 80 |
| Italy | 1995Q1 - 2019Q4 | 100 |
| Ireland | 1995Q1 - 2019Q4 | 100 |
| Israel | 1995Q1 - 2019Q3 | 99 |
| Japan | 1964Q4 - 2019Q4 | 221 |
| Korea | 1962Q4 - 2019Q4 | 229 |
| Luxembourg | 1999Q1 - 2019Q4 | 84 |
| Mexico | 1981Q1 - 2019Q4 | 156 |
| Netherlands | 1996Q1 - 2019Q4 | 96 |
| New Zealand | 1987Q2 - 2019Q4 | 131 |
| Norway | 1978Q1 - 2019Q4 | 168 |
| Portugal | 1995Q1 - 2019Q4 | 100 |
| Poland | 1995Q1 - 2019Q4 | 100 |
| Russia | 2003Q1 - 2019Q3 | 67 |
| Spain | 1995Q1 - 2019Q4 | 100 |
| South Africa | 1965Q1 - 2016Q4 | 208 |
| Switzerland | 1970Q1 - 2019Q4 | 200 |
| Sweden | 1993Q1 - 2019Q4 | 108 |
| Thailand | 1993Q1 - 2019Q3 | 107 |
| United States | 1952Q1 - 2019Q3 | 271 |
| United Kingdom | 1963Q1 - 2017Q3 | 219 |
| Total | | 4634 |

## A.2 GDP Credit Gap Regressions

**Table XI**

**Regression of Real Credit on Real GDP, $p = 3$**

This table reports the results of regression (10) of changes in the first difference of real credit on changes in the first differences of real GDP with 3 lags included. The constant is included but not reported to conserve space. Statistical significance is based on the z-test with the bootstrapped standard error of Section 5.5. The standard error is also not reported. The number of bootstraps is set to 1000. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| | $\Delta gdp_t$ | $\Delta gdp_{t-1}$ | $\Delta gdp_{t-2}$ | $\Delta gdp_{t-3}$ |
|---|---|---|---|---|
| Country | (1) | (2) | (3) | (4) |
| Australia | 0.326 | 0.032 | 0.319 | 0.386** |
| Austria | 0.333** | 0.335* | 0.416** | −0.065 |
| Argentina | 0.157 | −0.522** | 0.793*** | 0.047 |
| Belgium | 0.055 | −0.176 | 0.007 | 0.645 |
| Brazil | 0.076 | 0.626*** | 0.179 | 0.222 |
| Canada | 0.430 | −0.043 | 0.100 | 0.078 |
| Chile | −0.090 | −0.391 | 0.684** | 0.453 |
| Colombia | 0.775*** | −0.024 | 0.589* | 0.160 |
| Czech Republic | 0.397 | 0.079 | −0.501* | 0.688** |
| Denmark | 0.110 | 0.158 | 0.280 | −0.059 |
| France | 0.317** | 0.093 | −0.069 | 0.578*** |
| Finland | 0.061 | −0.154 | 0.143 | 0.148 |
| Germany | 0.079 | 0.024 | 0.062 | 0.037 |
| Greece | 0.417** | 0.245** | 0.111 | 0.568*** |
| Hungary | −0.575 | −0.139 | 1.232*** | −0.051 |
| Indonesia | 1.288 | 1.939 | 2.724* | 1.081 |
| Italy | 1.089*** | −0.712*** | 0.438** | 0.157 |
| Ireland | 0.843** | 0.025 | −0.173 | 0.009 |
| Israel | 0.450 | 0.185 | −0.008 | 0.059 |
| Japan | 1.023*** | 0.015 | −0.041 | −0.047 |
| Korea | 0.463*** | −0.008 | 0.336*** | −0.031 |
| Luxembourg | 0.489 | 0.286 | 0.097 | −0.042 |
| Mexico | 0.692** | −0.165 | 0.874*** | 0.669*** |
| Netherlands | 0.798*** | −0.491*** | 0.254 | 0.010 |
| New Zealand | 0.213 | 0.226 | 0.423** | −0.028 |
| Norway | 0.244* | 0.119 | 0.125 | 0.106 |
| Portugal | 0.304 | −0.070 | 0.374** | 0.642*** |
| Poland | 0.482** | −0.127 | 0.098 | 0.251 |
| Russia | −0.692 | 0.488 | 0.299 | 1.253* |
| Spain | 0.881* | −0.173 | 0.715*** | 0.813** |
| South Africa | 0.591** | 0.149 | 0.359 | 0.273 |
| Switzerland | 0.264 | 0.014 | −0.025 | −0.121 |
| Sweden | −0.426* | 0.200 | −0.043 | 0.004 |
| Thailand | 0.005 | 0.252* | 0.211* | 0.070 |
| United States | 0.247*** | 0.316*** | 0.111 | 0.287*** |
| United Kingdom | 0.401** | 0.626** | −0.059 | 0.460*** |

**Table XII**

## Regression of Real Credit on Real GDP, $p = 2$

This table reports the results of regression (10) of changes in the first difference of real credit on changes in the first differences of real GDP with 2 lags included. The constant is included but not reported to conserve space. Statistical significance is based on the z-test with the bootstrapped standard error of Section 5.5. The standard error is also not reported. The number of bootstraps is set to 1000. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Country | $\Delta gdp_t$ (1) | $\Delta gdp_{t-1}$ (2) | $\Delta gdp_{t-2}$ (3) |
|---|---|---|---|
| Australia | 0.266 | 0.103 | 0.373* |
| Austria | 0.330** | 0.322* | 0.397** |
| Argentina | 0.151 | −0.510** | 0.804*** |
| Belgium | −0.064 | −0.170 | 0.396 |
| Brazil | 0.304 | 0.297 | 0.368* |
| Canada | 0.431 | −0.031 | 0.126 |
| Chile | −0.054 | −0.446 | 0.896*** |
| Colombia | 0.795*** | 0.028 | 0.603** |
| Czech Republic | 0.480* | −0.047 | 0.039 |
| Denmark | 0.105 | 0.148 | 0.273 |
| France | 0.255* | 0.248* | 0.202* |
| Finland | 0.089 | −0.138 | 0.163 |
| Germany | 0.082 | 0.026 | 0.066 |
| Greece | 0.630*** | 0.444*** | 0.137 |
| Hungary | −0.499 | −0.154 | 1.260*** |
| Indonesia | 1.593 | 1.936 | 2.326 |
| Italy | 1.063*** | −0.682*** | 0.518*** |
| Ireland | 0.846** | 0.031 | −0.173 |
| Israel | 0.426 | 0.195 | 0.077 |
| Japan | 1.060*** | 0.051 | −0.008 |
| Korea | 0.462*** | 0.002 | 0.318*** |
| Luxembourg | 0.499 | 0.238 | 0.067 |
| Mexico | 0.439 | −0.003 | 0.709*** |
| Netherlands | 0.792*** | −0.470*** | 0.264* |
| New Zealand | 0.193 | 0.216 | 0.407** |
| Norway | 0.248* | 0.120 | 0.100 |
| Portugal | 0.391** | 0.105 | 0.533*** |
| Poland | 0.644*** | 0.091 | 0.167 |
| Russia | −0.992 | 0.600 | 1.349* |
| Spain | 0.995** | −0.203 | 1.321*** |
| South Africa | 0.621** | 0.228 | 0.361 |
| Switzerland | 0.260 | −0.009 | −0.021 |
| Sweden | −0.397* | 0.181 | −0.056 |
| Thailand | 0.000 | 0.300** | 0.210** |
| United States | 0.243*** | 0.347*** | 0.195*** |
| United Kingdom | 0.439** | 0.721*** | −0.068 |

## A.3 Real Credit BN Decompositions

**Table XIII**

**Results BN decomposition of Real Credit, $p = 3$**

This table reports the results of the Beveridge-Nelson (BN) decomposition of real credit with 3 lags included. The decomposition is estimated with the Kalman Filter using (13) as measurement equation and (14) as state equation. Statistical significance is based on the z-test with the bootstrapped standard error of Section 5.5. The standard error is not reported to conserve space. The number of bootstraps is set to ???. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Country | $\mu$ (1) | $\phi_1$ (2) | $\phi_2$ (3) | $\phi_3$ (4) |
|---|---|---|---|---|
| Australia | 0.013*** | 0.252*** | 0.263*** | 0.000 |
| Austria | 0.007 | 0.100 | 0.000 | 0.000 |
| Argentina | −0.004 | −0.169 | −0.000 | 0.000 |
| Belgium | 0.012*** | 0.105 | 0.285*** | −0.000 |
| Brazil | 0.011*** | 0.101 | −0.000 | −0.000 |
| Canada | 0.012*** | 0.187*** | 0.172*** | 0.000 |
| Chile | 0.016*** | 0.324*** | 0.000 | 0.000 |
| Colombia | 0.018*** | 0.175 | 0.316*** | 0.001 |
| Czech Republic | 0.007*** | 0.151 | 0.000 | 0.000 |
| Denmark | 0.009 | 0.193 | 0.216*** | 0.000 |
| France | 0.010*** | 0.021 | 0.273*** | −0.000 |
| Finland | 0.007*** | 0.368*** | 0.000 | 0.000 |
| Germany | 0.004 | 0.162 | 0.207*** | 0.000 |
| Greece | 0.010** | 0.187** | 0.278** | 0.334*** |
| Hungary | 0.014*** | 0.007 | 0.172** | 0.003*** |
| Indonesia | 0.017*** | 0.009 | 0.000 | −0.000 |
| Italy | 0.006*** | 0.055 | 0.555*** | 0.000 |
| Ireland | 0.024*** | 0.148 | 0.000 | 0.000 |
| Israel | 0.011*** | 0.028 | 0.276*** | −0.003*** |
| Japan | 0.010*** | −0.337* | −0.434*** | −0.004 |
| Korea | 0.027*** | 0.215** | 0.209*** | 0.001 |
| Luxembourg | 0.021* | 0.630*** | 0.000 | −0.000 |
| Mexico | 0.006* | 0.046 | 0.282*** | −0.001 |
| Netherlands | 0.008 | 0.060 | 0.204*** | 0.000 |
| New Zealand | 0.011*** | 0.055 | 0.000 | 0.000 |
| Norway | 0.010*** | 0.285*** | 0.000 | −0.000 |
| Portugal | 0.008*** | 0.339*** | 0.226** | 0.258*** |
| Poland | 0.023*** | 0.295*** | 0.000 | 0.000 |
| Russia | 0.021*** | 0.159 | −0.000 | 0.000 |
| Spain | 0.011*** | 0.553*** | 0.273*** | 0.001** |
| South Africa | 0.008*** | 0.177** | 0.098 | 0.000 |
| Switzerland | 0.007*** | −0.050 | 0.106* | −0.000 |
| Sweden | 0.011*** | 0.122 | −0.000 | −0.000 |
| Thailand | 0.009*** | 0.165 | 0.365*** | 0.003*** |
| United States | 0.011*** | 0.163** | 0.626*** | −0.002 |
| United Kingdom | 0.011*** | 0.052 | 0.000 | 0.000 |

**Table XIV**

## Results BN decomposition of Real Credit, $p = 2$

This table reports the results of the Beveridge-Nelson (BN) decomposition of real credit with 2 lags included. The decomposition is estimated with the Kalman Filter using (13) as measurement equation and (14) as state equation. Statistical significance is based on the z-test with the bootstrapped standard error of Section 5.5. The standard error is not reported to conserve space. The number of bootstraps is set to 250. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Country | $\mu$ (1) | $\phi_1$ (2) | $\phi_2$ (3) |
|---|---|---|---|
| Australia | 0.013*** | 0.252*** | 0.263*** |
| Austria | 0.007*** | 0.100 | 0.000 |
| Argentina | −0.004 | −0.174 | −0.000 |
| Belgium | 0.012*** | 0.105 | 0.285*** |
| Brazil | 0.010*** | 0.131 | 0.000 |
| Canada | 0.012*** | 0.187*** | 0.172*** |
| Chile | 0.017*** | 0.331*** | 0.000 |
| Colombia | 0.018*** | 0.175 | 0.316*** |
| Czech Republic | 0.007*** | 0.151 | 0.000 |
| Denmark | 0.009*** | 0.193 | 0.216*** |
| France | 0.010*** | 0.021 | 0.273*** |
| Finland | 0.007*** | 0.368*** | 0.000 |
| Germany | 0.004*** | 0.162 | 0.207*** |
| Greece | 0.013*** | 0.323*** | 0.357*** |
| Hungary | 0.013*** | 0.011 | 0.188** |
| Indonesia | 0.017*** | 0.009 | 0.000 |
| Italy | 0.006*** | 0.055 | 0.555*** |
| Ireland | 0.024*** | 0.148 | 0.000 |
| Israel | 0.011*** | 0.034 | 0.285*** |
| Japan | 0.010*** | −0.335* | −0.429*** |
| Korea | 0.027*** | 0.215** | 0.209*** |
| Luxembourg | 0.021*** | 0.630*** | 0.000 |
| Mexico | 0.006* | 0.046 | 0.282*** |
| Netherlands | 0.008*** | 0.060 | 0.204*** |
| New Zealand | 0.011*** | 0.055 | 0.000 |
| Norway | 0.010*** | 0.282*** | −0.000 |
| Portugal | 0.009*** | 0.442*** | 0.305*** |
| Poland | 0.024*** | 0.326*** | −0.000 |
| Russia | 0.021** | 0.159 | −0.000 |
| Spain | 0.011*** | 0.553*** | 0.273*** |
| South Africa | 0.008*** | 0.177** | 0.098* |
| Switzerland | 0.007*** | −0.051 | 0.106* |
| Sweden | 0.011*** | 0.123 | 0.000 |
| Thailand | 0.009*** | 0.170 | 0.367*** |
| United States | 0.011*** | 0.162** | 0.628*** |
| United Kingdom | 0.011*** | 0.052 | 0.000 |