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On the long-run calibration of the Credit-to-GDP gap as a banking crisis predictor

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Abstract

The trend deviation of the Credit-to-GDP ratio ("Basel gap") is a widely used early warning indicator of banking crises. It is calculated with the one-sided Hodrick-Prescott filter using an extremely large value of the smoothing parameter λ. We recalibrate the smoothing parameter with panel data covering almost one and a half centuries and 15 countries. The optimal λ is found to be much lower than previously suggested. The 2008 crisis does not dominate the results. The long sample almost eliminates filter initialisation problems.

Keywords: Banking crises, early warning, Basel gap

JEL: G01, E44, N20

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1 Introduction

Kaminsky and Reinhart (1999) and Demirgüç-Kunt and Detragiache (1998) presented pioneering studies on banking crisis prediction. The topic has become highly policy relevant. In various jurisdictions, regulatory authorities have been mandated to increase banks' capital adequacy requirements if the risk of a banking crisis seems heightened. Since Drehmann et al (2010), it has been commonplace to use the so-called Basel gap as an indicator of systemic risks, when policy makers set this countercyclical capital buffer requirement. The Basel gap is the difference between the credit-to-GDP ratio and its trend. The trend is calculated with quarterly data by running the Hodrick-Prescott filter. When the predictive power of this indicator is backtested, nothing but data till the moment in time is used, and subsequent observations are dropped off. This method is often referred to as the one-sided filter. This indicator has been recommended for national macroprudential authorities by international bodies, such as the Basel Committee and the European Systemic Risk Board. Various studies, such as Detken et al (2014) and Tölö et al (2018), have found that this indicator would have been highly useful as an early warning signal of banking crises in the last few decades.

In most econometric studies, it has been commonplace to use the smoothing parameter $\lambda = 1600$, when the HP-filter is applied to quarterly data. However, Drehmann et al (2010) found that a much larger λ, namely 400 000, yields the most accurate early warning signs in banking crisis forecasting. The sample consisted of G20 and OECD economies between 1980 and 2009. When λ goes to infinity, the HP-filter converges to a linear trend filter. The paper by Drehmann et al (2010) was never published in a refereed journal, but according to Google Scholar data, it had been referred to 298 times by December 2018. Drehmann and Yetman (2018) provide additional evidence on the ability of this indicator to outperform certain other early warning indicators in banking crisis prediction. Interestingly, there is little if any further empirical evidence on the value of lambda.

The data used by Drehmann et al (2010) is rather short, when compared to how sticky the estimated trend is. This problem is particularly serious during the early part of the sample period; if one estimates the trend for, say, 1990 there is only one decade of data. There is little difference between setting λ = 400 000 and re-estimating a linear trend with data till each quarter. In order to have a more reliable idea about the potential benefits of using a very large λ, much longer time series would be useful.

This paper applies almost 150 years of panel data to test parametrizations. Two different methods indicate that the best crisis prediction ability over this sample period is found at a much lower λ than previously thought.

2 Data and method

In the following analyses, the so-called Jordà-Schularick-Taylor macrohistory database is the sole source of data. [3] There is more than a century of annual data for each country. Germany and Japan were excluded because of obvious data discontinuities during the Second World War. There are 76 crises in the sample. Canada is the only country that has not experienced at least one banking crisis both before and after WW2. Interestingly, there was no crisis in sample countries between the Second World War and the 1970s. The data are described in Tables 1 and 2.

[3] See http://www.macrohistory.net/JST/JSTdocumentationR3.pdf

Table 1. Variable description

Variable	Definition	Source
Credit	Total Loans to Non-financial Private Sector (nominal, local currency)	JST Macrohistory Database
GDP	Nominal GDP (local currency)	JST Macrohistory Database
Crisis dummy	Systemic Financial Crisis dummy 0-1 by Jorda-Schularick-Taylor.	JST Macrohistory Database
Pre-crisis dummy variable	1 for 1-3 years before first year of crisis; Empty for crisis year and for the subsequent four years; 0 otherwise.	Constructed from crisis dummy

Table 2. The first year of the data and number of crises

	Data from	Crises before WW2	Crises after WW2
Australia	1870	1	1
Belgium	1885	5	1
Canada	1870	1	0
Denmark	1870	5	2
Finland	1870	4	1
France	1900	3	1
Italy	1870	7	2
Netherlands	1900	4	1
Norway	1870	3	1
Portugal	1870	4	1
Spain	1900	6	2
Sweden	1871	4	2
Switzerland	1870	2	2
U.K.	1880	1	3
U.S.A.	1880	4	2

54 crises before WW2, 22 crises after WW2
Data for Germany and Japan have been excluded because of large variations around WW2.
Last year of data 2016 for each country
Data source: http://www.macrohistory.net/data/

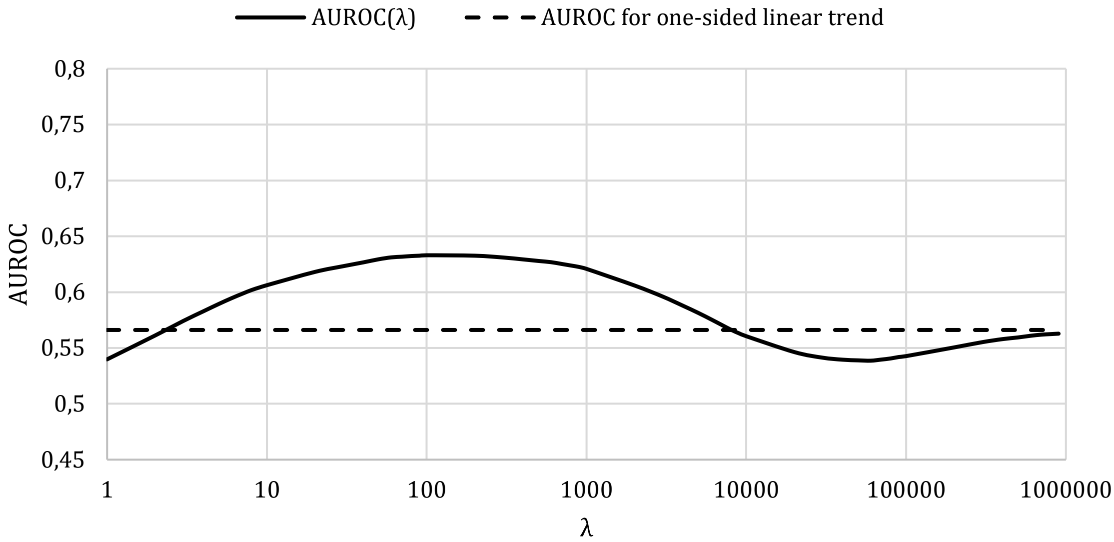
First, the performance of credit-to-GDP gaps as banking crisis predictors is evaluated by the AUROC. The method is described by e.g. Berge and Jordà (2011) and Detken et al (2014). AUROC lies between 0.5 and 1.0. A perfect indicator would have the AUROC = 1.0; each crisis would be forecasted, and no false alarms would be issued. If the value were 0.5, the indicator would be no better than random. Second, a traditional logit analysis is used to test the main conclusions. Unlike in many previous contributions, a very large number of values for the smoothing parameter λ are systematically tested. Moreover, the predictive power of gaps calculated with linear trends is calculated for comparison. When λ approaches infinity, trends based on one-sided HP-filters asymptotically approach these linear trends.

3 AUROC analyses

The explained variable is the pre-crisis dummy. Its value for a year t equals +1 if a systemic financial crisis broke out during the period t+1 to t+3. If there is an ongoing crisis, or if the latest crisis started less than five years earlier, the observation is excluded in order to eliminate the post-crisis bias. The credit-to-GDP gap is the sole explanatory variable. There are no country or year specific dummy variables and no macroeconomic control variables. There is no weighting of observations.

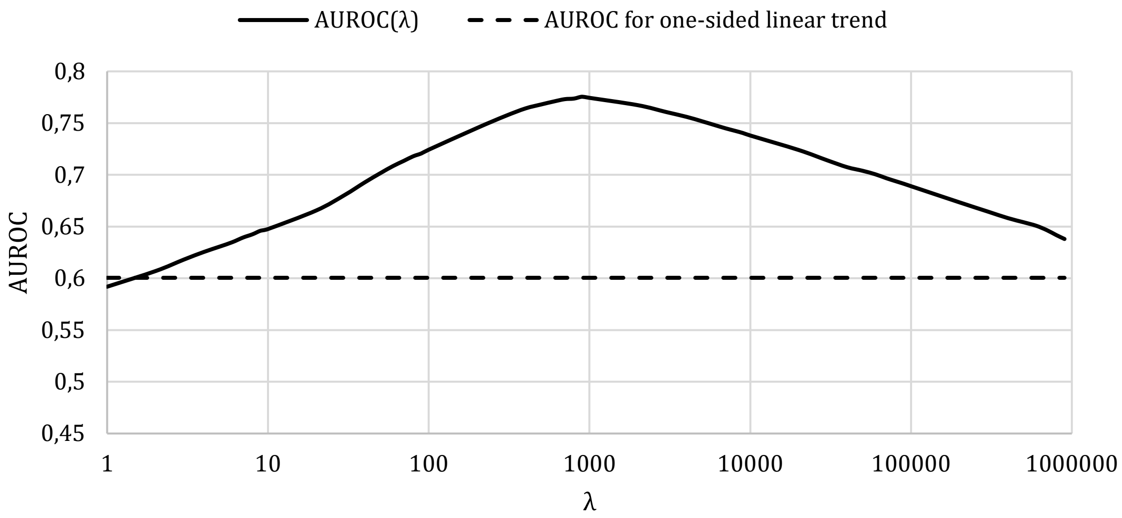
First, credit-to-GDP trends and respective gaps were estimated with the one-sided HP-filter for the entire sample. Previous analyses have focused on a handful of arbitrary lambda values, but now, a much more systematic approach is taken to cover a much wider range of potential options. Using the entire sample, it was found that the highest AUROC (0.633) is found at λ = 100 (See Fig 1). This parameter value obtained with annual data is not directly comparable with those obtained with quarterly data. One needs to multiply the annual λ by $4^4 = 256$ to get the corresponding λ at the quarterly frequency (see Ravn and Uhlig 2002). This result suggests that the optimal λ with quarterly data would be about 26 000, i.e. much lower than the current standard originally recommended by Drehmann et al (2010).

Figure 1: All crises, whole sample



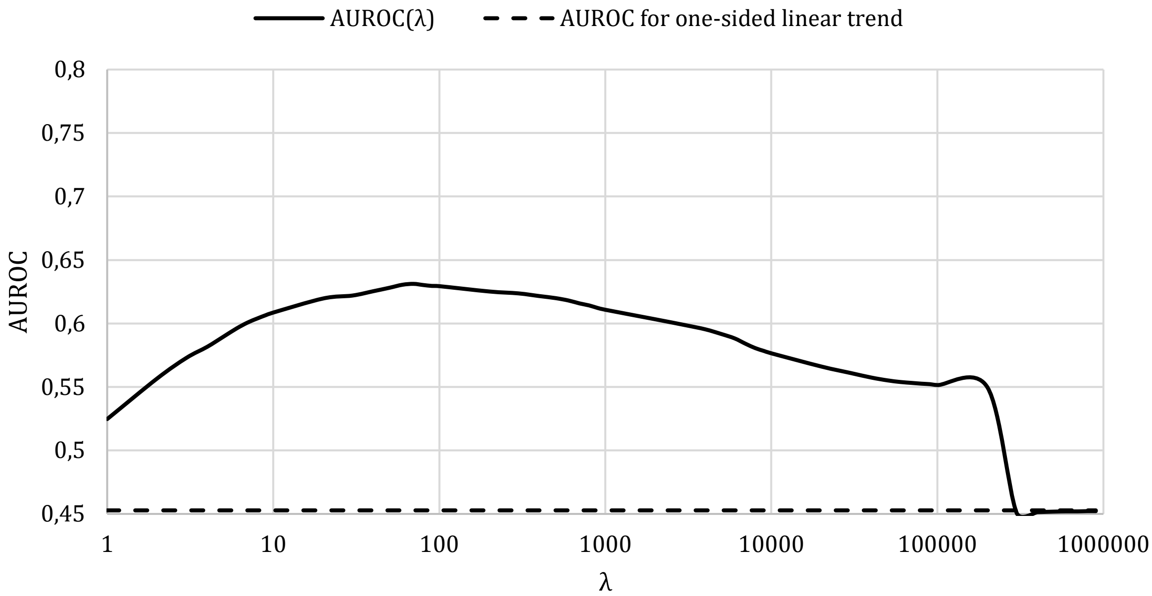
If we omit crisis observations before 1980, but use the entire sample for estimating credit-to-GDP trends, the highest AUROC is 0.776, i.e. much higher than with the entire sample. This optimum is found when annual λ equals 900, corresponding to a quarterly λ = 230 400 (See Figure 2). This is lower than the λ=400,000 recommended by Drehmann et al (2010) but still very large. However, conclusions based on crises after 1980 suffer from the problem that the number of independent crisis observations is much more limited than one might think. In 11 cases out of 22, a post WW2 crisis materialized in 2007-2008. It would be warranted to see them as national manifestations of the same crisis rather than independent events. (See Figure 2)

Figure 2: Trend estimations with whole sample, crisis prediction evaluated with crises after 1980



As can be seen in Figure 3, the highest fit with pre WW2 data is reached when λ is about 70, which corresponds to the quarterly λ value 17 900. (AUROC = 0.631) Trend gaps based on linear trends would be useless for this era. (See Figure 3)

Figure 3: Crises before WW2



4 Logit estimations

In the above analyses, both the explanatory variable, i.e. the trend gap, and the explained variable are strongly autocorrelated by construction. The explained variable always equals +1 for three consecutive years. Now, a more traditional method, namely the logit analysis, always with a fixed forecasting horizon, is used to test whether differences in the explanatory power of gaps obtained with different lambdas are statistically significant. Results are presented in Table 3.

In each equation, both the standard Basel gap (lambda = 1562 with annual data) and the one optimised with the entire sample (lambda =100) are used in parallel in crisis prediction. In each equation, the forecasting horizon is either one, two or three years. There are no year or country specific fixed effects, except for the years 1931 and 2008 in Equations 4-6 in Table 3. Cases where a crisis broke out one to four years earlier are excluded from the sample.

As can be seen in Table 3, there is little evidence the standard Basel gap would be of any use in banking crisis prediction, when one controls for the gap obtained with a much lower lambda value. However, Equation 1 weakly indicates that the Basel gap (lambda=1562) might improve forecasting accuracy at short forecasting horizons (equation 1). If the focus is on crises before 1970 (see equations 7-9), the standard gap is useless. If the analysis is restricted to crises after 1970, the first year in the sample used by Drehmann et al (2010), there is no evidence that either of the two gaps would clearly outperform the other one (equations 10-12).

Table 3. Logit analyses

	eq 1	eq 2	eq 3	eq 4	eq 5	eq 6	eq 7	eq 8	eq 9	eq 10	eq 11	eq 12
Gaps lagged by years	1	2	3	1	2	3	1	2	3	1	2	3
Years	1883-2016	1883-2016	1883-2016	1883-2016	1883-2016	1883-2016	1883-1969	1883-1969	1883-1969	1970-2016	1970-2016	1970-2016
GCRs	No	No	No	Yes	Yes	Yes	No	No	No	No	No	No
Constant	-3.45	-3.40	-3.37	-3.69	-3.67	-3.66	-3.34	-3.29	-3.32	-3.59	-3.67	-3.59
z-stat	-21.9	-22.9	-23.5	-22.4	-23.1	-23.1	-18.6	-19.6	-19.5	-13.7	-13.9	-13.7
Coeff Gap100	9.43	11.68	11.62	10.57	12.56	10.97	12.59	11.49	10.01	13.33	9.08	13.33
Z stat	2.2**	2.9***	3.0***	2.3**	3.3***	3.2***	3.0***	3.1***	3.1***	1.2	0.9	1.2
Coeff Gap1562	4.31	2.47	0.76	0.92	-0.49	-1.77	-0.31	-2.06	-3.37	5.35	7.58	5.35
z stat	1.6*	0.9	0.3	0.3	-0.2	-0.7	-0.1	-0.7	-1.4	1.0	1.6	1.0
Pseudo R2	0.045	0.038	0.026	0.188	0.188	0.187	0.022	0.014	0.010	0.090	0.110	0.090
LR-stat	23.231	19.660	12.913	96.233	96.071	93.113	7.191	4.693	3.024	16.881	20.629	16.881
Crises	60	60	58	60	60	58	38	38	36	22	22	22

Both the gap with lambda=100 and with lambda=1562 as explanatory variables in each specification. Both gaps lagged by the same nr of years.

* = 10% signific; **=5% signific.; ***=1% signific;

GCR = Global crisis dummy ; two separate dummy variables, one for 1931 and another for 2008 as control variables

Z stats based on Huber-White

5 Conclusions and discussion

The Basel gap's smoothing parameter λ was originally optimized with a panel data covering somewhat less than three decades. End-point problems of the one-sided HP-filter can be very serious when the value of λ is large and the sample is short. This paper presents results with a much longer sample, hopefully alleviating this problem. Moreover, the sample is not dominated by different national manifestations of the 2008 crisis.

The optimal λ is significantly lower if it is derived from a sample covering almost 150 years. The ability of credit-to-GDP gaps to foresee pre WW2 crises is weaker than its ability to forecast post-WW2 crises.

Crises after WW2 seem to be best predicted by a credit-to-GDP gap based on a very large λ, but logit analyses with data on a relatively recent sub-period indicate that using a parameter value optimised with the entire sample does not significantly weaken the results. Estimations with post WW2 crises may yield biased results because the 2008 global financial crisis drives the results too strongly. Instead, if one uses the entire sample, the standard Basel gap seems a significantly weaker predictor than a gap calculated with a much lower lambda value.

At least one previous observation suggests that the dynamics between credit, GDP and financial crises have not changed. Banking crises can be seen as extreme troughs of the financial cycle. The optimal λ would be related to the length of the cycle. It has been commonplace to conclude that the typical length of the financial cycle is between eight and twenty years (see e.g. Verona 2016 or Schüler et al 2017). Most empirical studies on cycle length use relatively short samples, but Aikman et al (2015) extended the sample to cover the late 19th century. The average financial cycle length was found to be about 13 years, which is comparable to results with much shorter data.

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