Exploring the Interplay Between Early Warning Systems' Usefulness and Basel III Regulation[1]

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Abstract

We analyse the ability of credit gap measures to predict banking crises by estimating the usefulness measure conditionally on policymaker's preferences. The results show that the signals based on the credit gap indicators are most useful when the policymaker's preferences regarding Type I and Type II errors are approximately equal. However, according to the current consensus, the preferences to avoid missing a crisis are higher than issuing a false signal. This means that the usefulness of the credit-gap-based early warning systems is likely to increase once the static Basel III regulative measures are implemented (assuming that their implementation results in lower financial crises' costs).

Keywords: Credit gap, Early warning system, Macro-prudential policy, Basel III regulation

JEL classification: E37, E51, G01, G28

[1] The opinions expressed in this paper are those of the authors only and do not necessarily reflect those of the Bank of Russia.

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1 Introduction

One of the key goals of central banks is the timely adoption of measures to prevent or mitigate financial crises, as well as to improve the financial stability of the banking system as a whole. In 2010, the Basel Committee on Banking Supervision published an assessment of the long-term economic impact of stronger capital and liquidity requirements introduced by Basel III. The Basel Committee's assessment of the long-term economic impact finds that there are clear, net, long-term economic benefits from increasing the minimum capital and liquidity requirements from their current levels in order to increase the safety and soundness of the global banking system. The benefits of higher capital and liquidity requirements accrue from reducing the probability of a financial crisis and the output losses associated with such crises. The benefits substantially exceed the potential output costs for a range of higher capital and liquidity requirements.

In order to reduce pro-cyclicality of credit, Basel III introduces a counter-cyclical capital buffer (CCyB) and proposes a credit-to-GDP gap as a guide for setting it. The useful properties of this indicator are confirmed generally for a broad array of countries and a long time span, which includes the most recent crisis. Researchers usually apply AUC-ROC analysis.[5] Drehmann and Juselius (2014) find that the credit-to-GDP gap outperforms other measures at long time horizons in the set of developed countries. Deryugina and Ponomarenko (2019) confirm that the standard credit gap indicator performs satisfactorily for emerging markets. Notably, such an assessment is based on certain assumptions about the policymakers' relative aversion to making different types of errors (i.e. missing the crisis or issuing a false signal). These preferences in turn depend on the expected severity of the financial crisis. There are, however, reasons to expect that this characteristic may change once the static regulations recommended by Basel III are implemented.

A related strand of research examines Basel III's macroeconomic effect. Behn and colleagues (2016) measure the gains of capital regulation as the expected output increase associated with the reduction in the likeliness and severity of banking crises. Budnik and colleagues (2019), working from the estimation of the FAVAR model, show that an increase in capital ratios have a sharply different impact on credit and economic activity depending on the way the bank adjusts. Arregui and colleagues (2013) find that changes in the regulation affect the expected probability of a crisis. Popoyan and colleagues (2016) develop an agent-based model and find that Basel III's prudential

[5] ROC (receive operating characteristics curve) is created by plotting the true positive rate against the false positive rate at various threshold settings; AUC is the area under the ROC curve.

regulation is the best policy mix to improve the stability of the banking sector and smooth output fluctuations. In the Basel Committee on Banking Supervision's review of the literature (BCBS 2019), the estimated marginal reduction in the annual probability of a crisis ranged across studies from as little as 0.03 percentage points to as much as 1.7 percentage points. Using quantile regressions applied to a panel dataset of advanced economies, Aikman and colleagues (2019) find that higher levels of banking system capital significantly improve GDP-at-risk in the medium term.

Therefore, there are good reasons to believe that the Basel III regulation changes the financial cycle's characteristics and reduces the severity of banking crises. As a result, policymakers' preferences regarding the early warning systems' performance will change. This paper develops the notion of credit gap performance as an early warning indicator (EWI) of a crisis under different policymakers' preferences and conjectures how its performance may change once the static part of the Basel III regulation is implemented.

2 Data

We use the cross-section of 21 countries (see Table 2 in Annex A). We use the Bank for International Settlements (BIS) database as the source for credit series (adjusted for breaks all sectors' credit to private non-financial sector). The availability of these data determines the composition of the data et. We use the Organisation for Economic Co-operation and Development (OECD) database for GDP and price series (GDP deflator if available and consumer prices otherwise). All data are seasonally adjusted using an X-12 procedure. Crisis periods are taken from Laeven and Valencia (2018).

3 Evaluation method

The predictive ability of EWIs is usually tested using ROC analysis, but this approach only presents an average measure of usefulness. A more comprehensive evaluation approach is the analysis based on the 'usefulness' measure, which is calculated conditionally on the policymaker's relative aversion to missed crises as opposed to false alarms. We believe that it is important to test the indicator's performance under different preferences. Notably, the introduction of Basel III macroprudential measures may change the macroeconomic performance, such as the probability and severity of banking crises, the credit gap and therefore possibly the policymaker's preferences. The 'usefulness' approach allows us to develop this idea.

We apply the ‘signals’ approach first developed by Kaminsky and colleagues (1998). In order to examine the performance of the credit gap, it is useful to design the following matrix (Table 1).

Table 1. Signalling matrix.

	Crisis (within 4-12 quarters)	No crisis (within 4-12 quarters)
Signal was issued	A	B
No signal was issued	C	D

In this matrix, A is the number of quarters in which the indicator issued a *good signal*; B is the number of quarters in which the indicator issued a *bad signal*; C is the number of quarters in which the indicator failed to issue a signal when the crisis occurred; and D is the number of quarters in which the indicator did not issue a signal when in fact there was no crisis. A waring signal is considered to be issued when the indicator exceed a threshold, which runs through the indicator’s distribution percentiles.[6]

The loss function of the policymaker is defined as (see Alessi and Detken, 2011):

$$L = \theta \frac{C}{A+C} + (1-\theta) \frac{B}{B+D}$$

θ is the parameter revealing the policymaker’s relative risk aversion between Type I (missing crisis) and Type II (false alarm) errors; C/(A+C) is the share of Type I errors; and B/(B+D) is the share of Type II errors.

Following the approach of Alessi and Detken (2011) we employ the ‘usefulness’ indicator to assess the models:

$$U = \min(\theta, 1-\theta) - L$$

A central banker can always realize a loss of min[θ ; 1 − θ] by disregarding the indicator (i.e. by issuing the signal either always or never). If θ is smaller than 0.5, the benchmark is obtained by ignoring the indicator, and never having any signals issued, so that A = B = 0. The resulting loss *L* is θ. If θ exceeds 0.5, the benchmark for the central bank is assuming that a signal is always issued C =

[6] Unlike Kaminsky et al. (1998), we follow Borio and Lowe (2002) and define the thresholds in terms of percentage point gaps. We examine 101 thresholds in these exercises in the range of [0; 1] in steps of 0.01.

D = 0. The resulting loss is $1 - \theta$. An indicator is then useful to the extent that it produces a loss lower than $\min[\theta ; 1 - \theta]$ for a given θ – that is, relying on the indicator reduces the loss compared to a situation in which the indicator is ignored.

4 Results

Credit gap indicators are estimated by applying a one-sided Hodrick–Prescott filter (λ=400000) to the log of the credit-to-GDP ratio recursively over the expanding window (with the minimum size of 12 quarters). We expect the credit gap to start issuing the warning signal 12 quarters before the crisis (crisis periods are here as defined in the work of Laeven and Valencia 2018) and exclude from the analysis four observations before the crisis and all of them during it, because warning signals are not truly useful any longer.

We adopt the signal approach and find the optimal thresholds by minimizing the lost function for different values of preference parameter θ.[7] As discussed in the work of Alessi and Detken (2011), it seems more relevant to obtain the results when the optimal threshold is imposed to be the same for all countries, and not for each country individually. So the calculations are conducted for the pool of 21 countries and 22 banking crisis episodes. In Figure 1, we report the usefulness indicators θ for the optimal thresholds calibrated for various θ.

The results show that the maximum value of the usefulness function is achieved when θ = 0.5. The preference parameter of 0.5 represents a policymaker who is equally concerned about missing crises than issuing false alarms. The usefulness decreases with a shift in both directions from θ = 0.5. This represents the increased difficulty of outperforming the static strategy in cases when the preferences are clear. In other words, the competitiveness of always (or never) issuing the signal strategy increases in case a policymaker clearly wants to avoid missing the crisis (or issuing a false signal).

Accordingly, the usefulness indicator is at its lowest for very low and very high θ. Its distribution is also asymmetrical. A small increase in the preferences not to miss the crisis (θ rise from 0.5 to 0.58) sharply affects the usefulness, but a further increase in θ affects it only slightly. At the same time, as the policymaker's preferences to avoid false signals increases, the usefulness of the credit gap decreases more slowly, but from some point ($\theta<0.13$), it makes no sense to use the signalling approach.

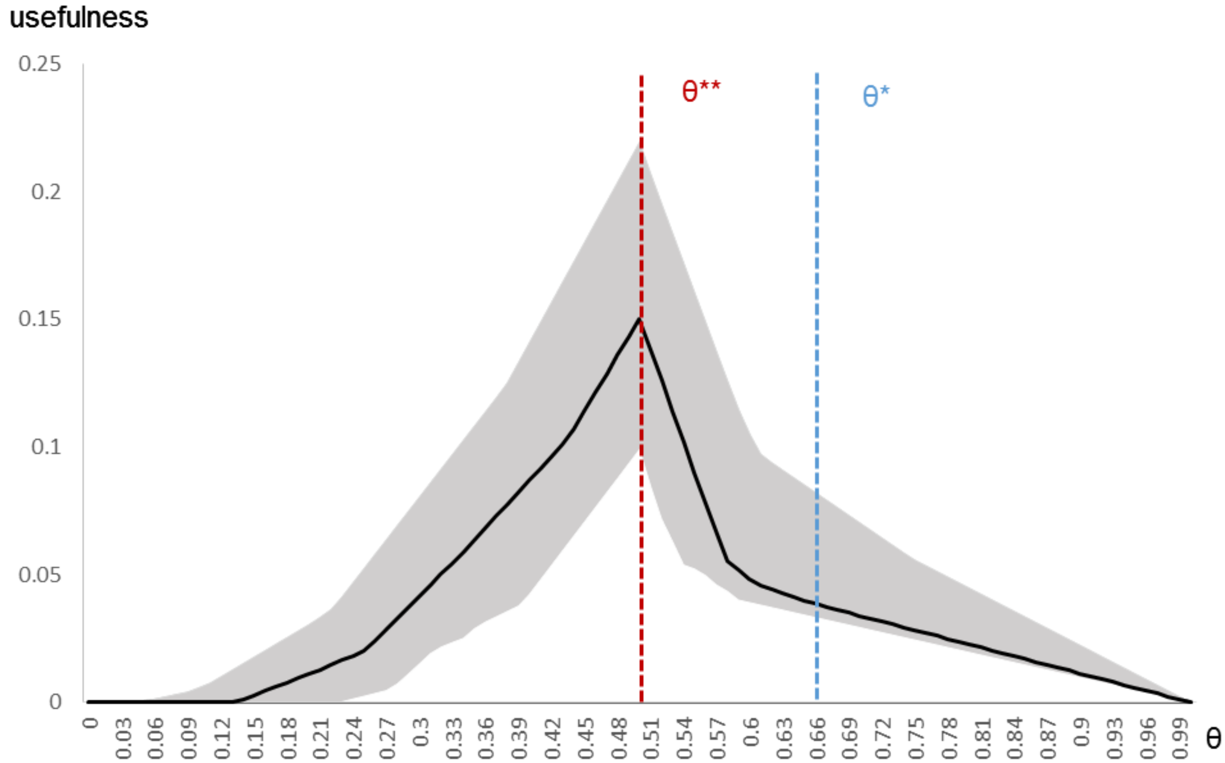
[7] Calculations are provided for all θ in the range of [0.01, 0.99] in steps of 0.01 to construct the smoothest usefulness function.

We also calculate the confidence interval with bootstrap simulations. To do this, we construct 1000 samples, organized by randomly taking observations of the credit gap and the corresponding moment of the crisis (or its absence). For each obtained sample, we apply the signal approach, and, as shown earlier, we construct the usefulness function. The range of values is used to calculate the confidence band for Figure 1. It shows significant uncertainty regarding the usefulness measure.

After the severe financial crisis, bearing in mind the high costs of a financial crisis manifested in the form of large output losses, rising unemployment and huge public deficits, the literature conventionally assumes that decision-makers give the crisis detection preference a higher weight – that is, set $\theta > 0.5$ (see, for example, Detken and Smets 2004; Alessi and Detken 2018). We may assume $\theta^* = 0.66$, meaning that the cost of missing a crisis is twice as high as the cost of issuing a false signal. At these preferences, the credit gap's usefulness is marginally positive.

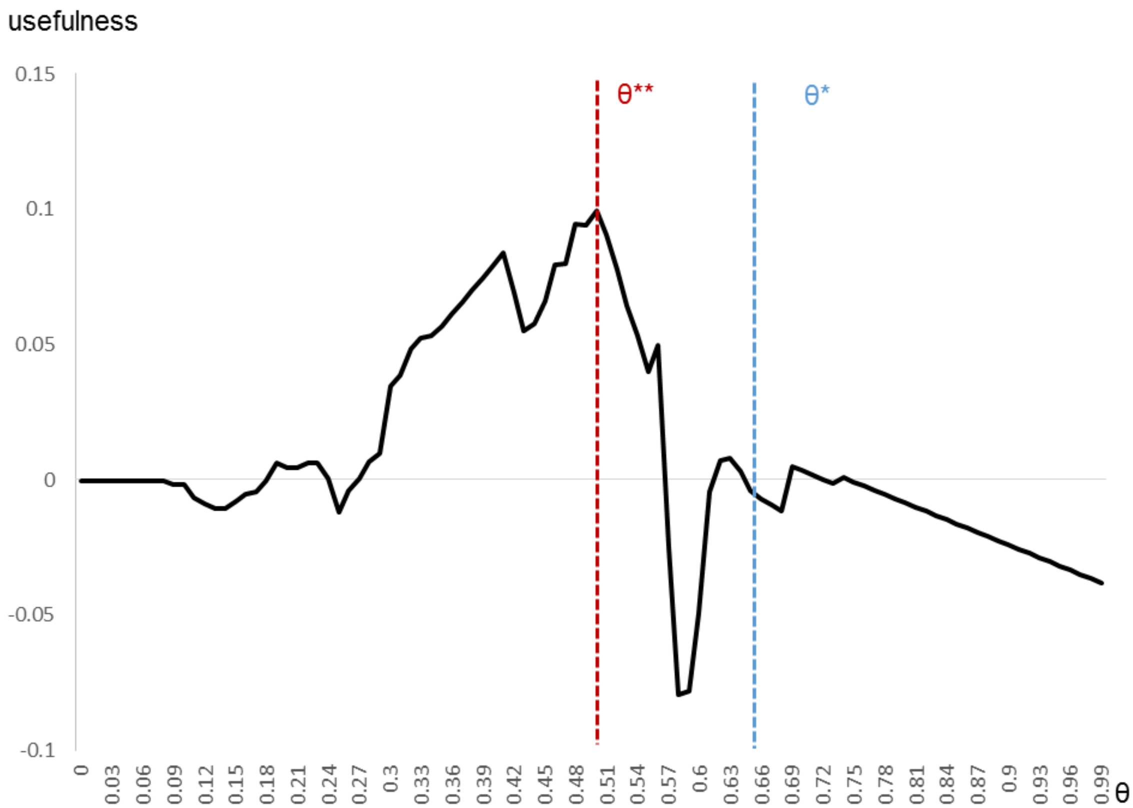
Let us now consider what will change after the introduction of the macroprudential regulation measures by Basel III and our assumptions about the credit gap performance in the new conditions. Presumably, the Basel III regulation (such as e.g. minimum static capital requirement CAR3) may reduce the severity of banking crises. For example, if we assume that the cost of a financial crisis will be halved after the implementation of Basel III's static capital requirements (see Annex B for the justification of such an assumption), we may assume $\theta^{**} = 0.5$. In these circumstances, the credit gap's usefulness increases significantly.

Figure 1. Usefulness indicator for different preferences



Next, we conduct a similar exercise to examine if the credit gap can be a good out-of-sample predictor of the crisis and apply the leave-one-out validation approach. Namely, we exclude data of one country (tested country) from the pool and estimate the optimal thresholds for each θ. These thresholds minimize losses for a truncated pool, and we expect that they are suitable for the tested country. Therefore, we evaluate A, B, C and D (from Table 1) assuming that the signal is issued if the credit gap of the tested country exceeds the threshold estimated at the previous step and is not issued otherwise. This procedure is repeated 21 times, excluding all countries in turn. Finally, we estimate the loss function and usefulness function using the average values of the A, B, C and D. The results are shown in Figure 2. They show that the out-of-sample signals based on the credit gap indicators are useful only for θ from 0.28 to 0.56. According to these results, the gain in usefulness of the EWIs after the implementation of Basel III may be even more dramatic.

Figure 2. Usefulness indicator for different preferences (out-of-sample)



5 Conclusions

We analyse the ability of credit gap measures to predict banking crisis by estimating the usefulness measure conditionally on policy-makers' preferences. The results show that the signals based on the credit gap indicators are most useful when the policy-maker's preferences regarding Type I and Type II errors are approximately equal. However, according to the current consensus, the preferences to avoid missing a crisis are higher than issuing a false signal. The static Basel III measures may potentially lead to a decrease in the severity of the crises and, accordingly, reduce the cost of missing a crisis. Interestingly, this means that there is an interplay between static and dynamic Basel III regulation mechanisms and that the usefulness of the credit gap measure as an EWI and the efficiency of CCyB as a macroprudential measure in general are likely to increase once the static Basel III regulation measures are implemented.

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Annex A. Dataset

Table 2. Cross-section of countries

Country	*Time sample*		*Crises*
	From	*To*	
Australia	Q1 1960	Q3 2016	-
Austria	Q1 1960	Q4 2016	2008 - 2012
Belgium	Q3 1970	Q3 2016	2008 - 2012
Canada	Q1 1960	Q3 2016	-
Denmark	Q1 1967	Q3 2016	2008 - 2009
Finland	Q3 1970	Q3 2016	1991 - 1995
France	Q3 1969	Q3 2016	2008 - 2009
Germany	Q1 1960	Q3 2016	2008 - 2009
Greece	Q1 1960	Q3 2016	2008 - 2012
Ireland	Q2 1976	Q3 2016	2008 - 2012
Italy	Q1 1960	Q3 2016	2008 - 2009
Japan	Q3 1964	Q3 2016	1997 - 2001
Korea	Q3 1962	Q3 2016	1997 - 1998
Netherlands	Q4 1960	Q3 2016	2008 - 2009
Norway	Q1 1960	Q3 2016	1991 - 1993
Portugal	Q1 1960	Q3 2016	2008 - 2012
Spain	Q4 1969	Q3 2016	1977 - 1981 2008 - 2012
Sweden	Q4 1960	Q3 2016	1991 - 1995 2008 - 2009
Switzerland	Q1 1960	Q3 2016	2008 - 2009
United Kingdom	Q4 1962	Q3 2016	2007 - 2011
United States	Q4 1951	Q3 2016	1988 2007 - 2011

Annex B. Modelling the effect of changes in capital requirements on financial crises' severity

To assess the impact of the capital requirement introduction on the change in expected depth of recession or the severity of future crises, we use the model calibrated by Miles and colleagues (2013) to match historical experience going back almost 200 years. The data are for the change in GDP per capita for a sample of 31 countries, and it starts, in some cases, in 1821 and continues to 2008. The number observations of annual GDP growth is almost 4,500.

In line with Miles and colleagues (2013), we assume that the first difference of the log of per capita GDP (Y) follows a random walk with a drift and two random components. To capture capital requirement effect, we include an additional shock τ_t, which represents development banking insolvency as a response to the serious economic crisis. Like Miles and colleagues (2013), we assume that generalized falls in the value of bank assets are driven by changes in the level of incomes in the economy. Insolvency occurs when losses on bank assets exceed bank equity.

$$\log(A_t) = \log(A_{t-1}) + \gamma + u_t + v_t + \tau_t$$

where A_t – income (or GDP), γ – average productivity growth.
$u_t \sim N(0, \sigma^2)$ represents the standard shocks in normal times.
v_t represents a financial shock. It equals zero in normal times, but make take a very large negative value -*b* with small probability *p* and symmetric shocks of lesser magnitude $\pm c$ with probability *q*.

$$v_t = \begin{cases} 0, & with\ probability\ (1-p-q) \\ -b, & with\ probability\ p \\ +c, & with\ probability\ q/2 \\ -c, & with\ probability\ q/2 \end{cases}$$

The third shock τ_t represents the probability of an economic downturn becoming a full-scale systemic financial crisis. It links the value of capital adequacy ratio *K* and GDP losses. If banks have enough capital during a recession, the banking crisis does not occur ($\tau_t = 0$), but it will happen otherwise. We implement this assumption as follows:

$$\tau_t = \begin{cases} \delta * (\log(A_{t-1}) - \log(A_{t-2}) + K), & \gamma + u_t + v_t + K < 0 \\ 0, & otherwise \end{cases}$$

We set $K = 3\%$ for the benchmark specification. Other parameters are reported in Table 3. Under this parametrization, the model generates the distribution of GDP growth rates that is close to the empirical distribution reported by Miles and colleagues (2013). This comparison is reported in Tables 3 and 4.[8]

Table 3. Model parameters

Description	Parameter	Value
Average productivity growth	γ	$2.21*10^{-2}$
Standard deviation of GDP growth	σ	$3.5*10^{-2}$
Annual probability of extreme financial shock	p	$0.035*10^{-2}$
Magnitude of extreme negative shock	b	$-38*10^{-2}$
Annual probability of standard financial shock	q	$3.1*10^{-2}$
Magnitude of standard financial shock	c	$11*10^{-2}$
Magnitude of financial crisis shock	δ	$1.7*10^{-2}$

Table 4. Statistics of artificial and empirical GDP growth rates

	Empirical	Artificial
Mean	1.81	1.85
Standard deviation	5.7	5.2
Skewness	-2.4	-2.6
Kurtosis	39	26

We proceed by conducting the following experiment. We change K from 3% to 10%, representing the increase in capital requirements in line with the Basel III recommendations. The new set of artificial GDP growth rates is computed, and several indicators of the severity of recessions in the alternative artificial datasets are compared. The first indicator we calculate is the unconditional probability of observing a decline in GDP larger than a threshold P (we test P=5% and P=10%). The

[8] The results presented in Tables 3-4 are based on 100000 artificial observations.

second indicator is the conditional probability of observing the decline larger than a threshold given that a recession takes place. The results are reported in Table 5. The estimates indicate that for *P*=5%, the recession severity indicators are approximately halved when *K* is increased from 3% to 10%. The drop is even more significant if *P*=10%. Arguably, these results may be regarded as a proxy for changes in the costs of a financial crisis under higher capital requirements. Accordingly, for the purpose of an early warning system's usefulness evaluation exercise, we assume that the losses associated with the Type I error (i.e. missing a crisis) may be twice as low under Basel III's capital requirements.

Table 5. Severity of recessions under different capital requirements

	Unconditional probability of recession		**Conditional probability of recession**	
Threshold *P*	>10%	>5%	>10%	>5%
Empirical	0.025	0.07	0.092	0.258
Artificial (*K*=3%)	0.026	0.057	0.096	0.212
Artificial (*K*=10%)	0.006	0.033	0.023	0.121