Anchoring Countercyclical Capital Buffers: The Role of Credit Aggregates*

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We investigate the performance of different variables as anchors for setting the level of the countercyclical regulatory capital buffer requirements for banks. The gap between the ratio of credit to GDP and its long-term backward-looking trend performs best as an indicator for the accumulation of capital, because this variable captures the build-up of systemwide vulnerabilities that typically lead to banking crises. Other indicators, such as credit spreads, are better at indicating the release phase, as they are contemporaneous signals of banking sector distress that can precede a credit crunch.

JEL Codes: E44, E61, G21.

1. Introduction

Financial boom-and-bust cycles are costly for the banks involved and for the economy at large. Between mid-2007 and end-2010, major global banking institutions reported cumulative write-downs to the tune of $1.3 trillion. Output declined dramatically. The cumulative impact over 2008–10 on economic activity in the harder-hit

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advanced economies exceeded 10 percent of their respective GDP, and average unemployment rates shot up from about 5 percent to nearly 9 percent. The repercussions of the crisis were felt by countries outside its epicenter. Between mid-2008 and mid-2009, world GDP contracted by 1.6 percent for the first time in recent memory (IMF World Economic Outlook 2011). Unsurprisingly, the experience added impetus to policymakers' and academic economists' efforts to better understand the mechanisms that drive financial system procyclicality and to devise policy tools that can mitigate it.

This paper examines one such tool: time-varying regulatory capital buffers for banks. It focuses specifically on the choice of indicators that can provide a reliable guide for regulatory capital requirements to dampen banks' procyclical behavior, restraining risk taking during booms and cushioning financial distress during busts. We analyze the behavior of a wide range of possible indicator variables around episodes of systemic banking crises, drawing on the empirical evidence from more than forty crises in thirty-six countries.

The analysis focuses separately on the run-up phase to the crisis and on the phase that follows its outbreak. This is necessary because financial stability risks tend to build up gradually in good times, but their consequences materialize quite suddenly.[1] This also means that the requirements for the policy tool differ between these two phases. Early-warning properties are very important in the phase in which vulnerabilities build up, so as to activate policy tools in time to influence behavior. By contrast, the ability to signal banking sector stress in real time is critical in guiding the tool during a crisis.

We find that the variable that performs best as an indicator for the build-up phase is the gap between the ratio of credit to GDP and its long-term trend (the credit-to-GDP gap). Across countries and crisis episodes, the variable exhibits very good signaling properties, as rapid credit growth lifts the gap as early as three or four years prior to the crisis, allowing banks to build up capital with sufficient lead time. In addition, the gap typically generates very low "noise," by not producing many false warning signals that crises are imminent.

The credit-to-GDP gap, however, is not a reliable coincident indicator of systemic stress in the banking sector. In general, a prompt and sizable release of the buffer is desirable. Banks would then be free

[1] Jiménez and Saurina (2006) provide empirical evidence for Spain.

to use the capital to absorb write-downs. A gradual release would reduce the buffer's effectiveness. Aggregate credit often grows even as strains materialize in the banking system. This reflects in part borrowers' ability to draw on existing credit lines and banks' reluctance to call loans as they tighten standards on new ones. A fall in GDP can also push the ratio higher. Aggregate credit spreads do a better job in signaling stress. However, their signal is very noisy: all too often they would have called for a release of capital at the wrong time. Moreover, as spread data do not exist for a number of countries, their applicability would be highly constrained internationally.

We conclude that it would be difficult for a policy tool to rely on a single indicator as a guide across all cyclical phases. It could be possible to construct rules based on a range of conditioning variables rather than just one, something not analyzed in this paper. However, it is hard to envisage how this could be done in a simple, robust, and transparent way. More generally, our analysis shows that all indicators provide false signals. Thus, no fully rule-based mechanism is perfect. Some degree of judgment, both for the build-up and particularly for the release phase, would be inevitable when setting countercyclical capital buffers in practice. That said, the analysis of the political economy of how judgment can be incorporated in a way that preserves transparency and accountability of the policymakers in charge goes beyond the scope of this paper.

While the discussion in the paper is exclusively in terms of the design of a countercyclical buffer tool, the analysis applies to any time-varying instrument aimed at reducing procyclicality that relies on indicator variables. The behavior of different indicator variables in the build-up and release phases is the key parameter determining their suitability.

The rest of the paper is organized as follows. Section 2 frames the issues by discussing the objectives of the countercyclical capital buffer and placing this work in the broader context of the literature. Section 3 discusses the desirable characteristics of an indicator variable. Section 4 describes the candidate variables we analyze and explains the data used in constructing them. Section 5 explains the statistical exercises, conducted separately for the build-up and release phases. Section 6 presents the results of some robustness analysis, concerning the choice of detrending parameters and dealing with the cross-country exposures of banks. The last section concludes.

2. The Main Objective of Countercyclical Capital Buffers

Financial system procyclicality refers to the mutually reinforcing interactions between the real and financial sectors of the economy that tend to amplify the business cycle and that are often at the root of financial instability.[2] These interactions are most evident during periods of financial stress. A weakened financial system facing strains cannot absorb further losses without retrenching from risk and credit intermediation, leading to fire sales and a "credit crunch."[3] Arguably, however, the seeds of the strains that materialize during downturns are sowed earlier, during the preceding upswing. Episodes of severe financial sector stress are typically preceded by extended periods of unusually low perceived risk, marked by booming financial sector activity and strong asset price growth (e.g., Reinhart and Rogoff 2009). Amplifying feedback mechanisms can be as potent in the expansion phase as they are in cyclical downturns.

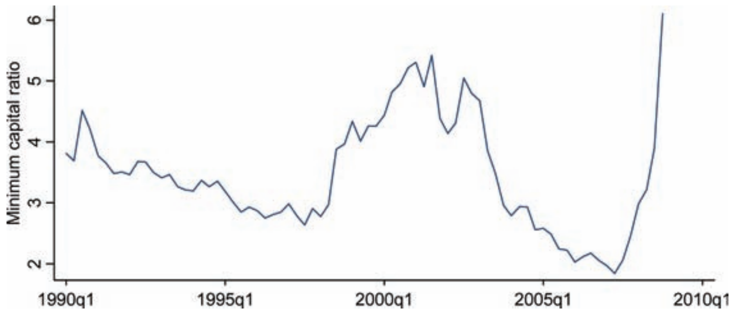
There is a long tradition, most prominently expressed by Minsky (1982) and Kindleberger (2000), which sees financial crises as the result of mutually reinforcing processes between the financial and real sides of the economy. In this view, financial imbalances are driven by, but also feed, an unsustainable economic expansion, which manifests itself in unusually rapid growth of credit and asset prices. As the economy grows, cash flows, incomes, and asset prices rise; risk appetite increases; and external funding constraints weaken. This, in turn, facilitates risk taking. The financial system typically does not build up sufficient capital and liquidity buffers during benign economic conditions, when it is easier and cheaper to do so, in order to deal with more challenging times. At some point, imbalances have to unwind, potentially causing a crisis, characterized by large losses, liquidity squeezes, and possibly a credit crunch.

Financial system procyclicality can be traced to two fundamental sources (e.g., Borio 2003, Bank for International Settlements 2009). The first source is limitations in risk measurement. The typical

[2]For a fuller discussion, see Borio, Furfine, and Lowe (2001), Brunnermeier et al. (2009), and references therein.

[3]For evidence related to the recent crisis, see Ivashina and Scharfstein (2010).

Figure 1. Procyclical Assessment of Credit Risk



Notes: The capital charge (in percentage points) is a measure of portfolio credit risk based on the risk weights embedded in the internal ratings-based (IRB) methodology of Basel II. The IRB formula is applied to the exposures in a credit portfolio that includes rating categories ranging from AAA to Caa3. We follow Catarineu-Rabell, Jackson, and Tsomocos (2005) in setting the portfolio shares of each rating class. For each exposure and observation in the sample, we proxy the probability of default with the expected default frequency taken from the database of Moody's KMV.

parameters underlying risk-measurement practices tend to be procyclical (e.g., Gordy and Howells 2006). The second, complementary, source is distortions in incentives (e.g., Rajan 2005). Principal-agent issues result in conflicts of interest between providers and users of funds. In addition, externalities in behavior and strategic complementarities suggest that actions that may be rational from the perspective of individual agents may collectively result in undesirable outcomes. Short horizons by private decisionmakers enhance the impact of both fundamental sources on procyclicality.

Figure 1 illustrates the cyclicality in risk measures, using as a metric the capital charge that would apply on a hypothetical credit portfolio. The calculation applies the risk weights in the internal ratings-based (IRB) methodology of Basel II and uses market-derived probabilities of default as the main input. The cyclicality of the risk measure is clearly apparent. Focusing on the most recent period, capital would have reached its all-time minimum just before the crisis in 2007, after which it would have increased rapidly.

Against this backdrop, what should be the objective of countercyclical policy tools and, in our specific case, of countercyclical bank capital requirements?

We distinguish three objectives that vary in their degree of ambition for countercyclical policies. The first, most ambitious, objective is to smooth the *business cycle* through the influence of capital requirements on banks, i.e., to use them as a demand management tool. Setting such an objective is commensurate to calibrating time-varying prudential capital requirements to achieve a *macroeconomic goal*. A less ambitious objective is to smooth the financial (credit) cycle. We think of this approach as using capital requirements as a means of achieving a *broad macroprudential goal*. The third, and least ambitious, objective is simply to protect the banks from the build-up of systemwide vulnerabilities. We call this a *narrow macroprudential goal*, designed to strengthen systemic resilience without taking explicit account of its influence on the financial and business cycles.

The choice of objective is not independent of the nature of the instrument. We argue that it would be prudent for the objective of the countercyclical buffer to be relatively modest. This argument is based both on the effect of capital requirements on economic behavior and on the current state of our knowledge of the quantitative links between capital requirements, credit availability, and economic activity.

A macroeconomic stabilization objective would make the analysis in this paper superfluous: a natural candidate to anchor the instrument would be a standard measure of economic activity, such as GDP growth. At the same time, however, choosing this objective would overestimate the current state of our knowledge about the influence of capital requirements on the credit cycle and output. The literature on dynamic models that combine financial and real sectors is growing (e.g., Bernanke, Gertler, and Gilchrist 1996, Van den Heuvel 2008, Gerali et al. 2010, and Meh and Moran 2010).[4] However, the models are still very much in their infancy and do not yet match the level of maturity and general acceptance that characterize the prevailing paradigm in the field of monetary policy.[5] Moreover, our empirical understanding of the impact of changes in

[4]Other examples that build on the financial accelerator literature developed by Bernanke and Gertler (1989) and the credit cycles model of Kiyotaki and Moore (1997) include Lorenzoni (2008) and Korinek (2011). Zhu (2008) analyzes a dynamic model linking bank capital to credit and output.

[5]A representative example of the prevailing paradigm for the analysis of monetary policy is Woodford (2003).

regulatory instruments (such as capital requirements) on lending, asset prices, and, by extension, aggregate expenditure and GDP is still very limited. To be sure, the literature on the credit channel has largely supported the notion that higher capital requirements would have a negative influence on the supply of credit, at least for institutions that are weakly capitalized and illiquid (for surveys, see VanHoose 2007 and, more recently, Gambacorta and Marques-Ibanez 2011).[6] But it is rather uninformative about whether they would have a similar effect during a boom. Also, the link between credit and GDP tends to be time varying and dependent on the financial structure of the economy.[7]

Similar arguments would apply to adopting the broad macroprudential objective of smoothing the credit cycle. In this case, the relevant objections would concern only the link between capital requirements, on the one hand, and credit supply and bank risk taking, on the other, and not the impact of the requirements on aggregate demand and GDP. At the same time, however, the design of the instrument would at least require an operational definition of the credit (or financial) cycle.

The literature on the credit cycle and its relationship to the business cycle provides little guidance. It relies mostly on simple setups in which the credit cycle is *fully aligned* with the business cycle. For example, in Kashyap and Stein (2004) a social planner wants not only to protect the economy from externalities arising from possible bank defaults but also to ensure that positive net-present-value projects are funded. However, in states where banks experience high loss rates and raising capital is very costly, the supply of credit is constrained. In these cases, the optimal balance for a policymaker is to accept higher failure rates. Repullo and Suarez (2009) identify a similar trade-off.

Importantly, in these examples good and bad states are identified respectively with GDP growth and recession periods. Consequently, *by construction*, the best indicator variable to anchor countercyclical

[6]Taking the results of Gambacorta and Marques-Ibanez (2011) at face value, Drehmann and Gambacorta (2011) show that countercyclical capital buffers would have significantly reduced bank lending in Spain.

[7]For a discussion in the euro-area context, see Angelini, Kashyap, and Mojon (2003).

Table 1. Real Credit Growth during Recessions (in percent)

	Mean	Percentile							# Obs.
		5%	10%	25%	50%	75%	90%	95%	
All Data	0.3	−10.7	−5.4	−1.9	1.0	3.7	6.2	8.8	156
Until 2007:Q2	−0.1	−11.8	−6.8	−2.1	0.3	3.6	6.3	8.9	124
Current Crisis	1.9	−4.1	−1.6	−0.2	1.6	4.1	5.4	7.8	32

Note: The table shows the distribution of average real credit growth during recessions, defined as periods of at least two consecutive quarters of negative real GDP growth.

capital buffers is a measure of the business cycle, such as GDP growth. This is true regardless of whether one adopts a broad or a narrow objective. Repullo and Saurina (2011) argue that GDP growth should be the guide for countercyclical capital requirements using essentially this rationale.

Empirically, however, the business and credit cycles do not coincide. For instance, Koopman and Lucas (2005) show that at typical business-cycle frequencies, around four to eight years, there is no cyclical co-movement between GDP and default rates, although some correlation is evident at longer horizons, of eleven to sixteen years. In addition, Mendoza and Terrones (2008) find that output increases during credit booms but that output booms need not involve credit booms, which tends to reduce the degree of co-movement of the two cycles. Finally, Aikman, Haldane, and Nelson (2010) as well as Claessens, Kose, and Terrones (2011) conclude that financial cycles are longer and more pronounced than business cycles.

Table 1 illustrates how business and credit cycles are not fully synchronous. Over the period covered by our data (see next section), the average correlation between the growth rates of real credit and real GDP across the forty countries we study is about 44 percent. This is significantly different from zero, but it hardly suggests a close alignment of the two cycles. Furthermore, and more to the point for the focus of this paper, not every recession is characterized by serious credit constraints. As a rough measure, table 1 shows that for more than half of the recessions in our sample, real credit growth is actually positive.

Hence, in this paper we adopt the third and least ambitious objective, which focuses exclusively on protecting the banks from the build-up of systemwide vulnerabilities. The countercyclical capital buffer tries to accomplish this by actively encouraging the build-up of buffers in boom times (when risks are taken on but, arguably, are not fully reflected in prices) and by releasing them in bad times (when the market price of risk shoots up once losses materialize). Clearly, to the extent that a policy instrument succeeds in this narrower objective, it is also likely to make a contribution to the broader goal of smoothing the financial and business cycles. This, however, is seen as a collateral benefit rather than as the principal objective.

3. Key Characteristics of an Effective Instrument

What are the criteria that should guide the choice of the anchor variable? Given the objective of strengthening the defenses of banks against systemic risk, the criteria for the indicator variable follow from the desirable features of the countercyclical buffer.

The main idea of a countercyclical buffer is to promote the build-up of sufficient capital cushions in the banking system during the boom phase of the financial cycle and to encourage their use during stressful periods, thereby easing the strains in credit supply. From this perspective, the instrument should be designed to meet four criteria:

(i) It should signal the proper *timing* for the accumulation and release of the capital buffer. This means that it should identify good and bad times.

(ii) It should ensure that the *size* of the buffer built up in good times is sufficient to absorb subsequent losses, when these materialize, without triggering serious strains.

(iii) It should be *robust to regulatory arbitrage*. This includes being difficult to manipulate by individual institutions as well as being applicable to banking organizations that operate across borders.

(iv) It should be as *rule based as possible*, *transparent*, and *cost-effective*.

The first criterion relates to the all-important issue of characterizing the cycle against which the instrument should lean (act countercyclically). This is the focus of the empirical analysis in this paper. It is key, therefore, to characterize what we mean by "good times," when the capital buffers need to be accumulated, and by "bad times," when they should be used to absorb losses.

Kashyap and Stein (2004) and Repullo and Suarez (2009) argue that bad times are periods when banks experience high losses and the banking sector is a source of credit constraints, which in their setup coincides with GDP declines. This suggests that bad times can be identified by a mix of two factors: some measure of banks' aggregate gross losses and of the extent to which banks are a source of credit tightening. The transition from bad to good times could be identified in a similar way, but its precise timing is less critical. This is because of the asymmetry in the financial cycle. The emergence of financial strains tends to be very abrupt and, typically, comes as a surprise. It is therefore essential that the buffer is released sufficiently promptly and in sufficient amounts. By contrast, the transition from bad to good times is much more gradual.

Finding good measures for losses and credit conditions is often problematic. Aggregate loss series are not widely available and accounting rules tend to distort their timing. In practice, loan-loss provisions tend to behave as lagging rather than contemporaneous indicators of bank distress. Credit conditions are measured in several countries by surveys, such as the Loan Officer Opinion Survey in the United States. These surveys relate to changes in credit conditions, not to the absolute degree of tightness. By construction, therefore, they can point to an easing of conditions even as credit supply is severely constrained.[8] In addition, survey-based measures could be subject to strategic reporting were they to be used to anchor countercyclical capital requirements. Finally, they are not widely available internationally.

Instead of relying on banking sector losses combined with a measure of credit conditions, we use historical banking crises as empirical

[8]Even though it measures only the change in credit conditions, the net-tightening series in the United States were found to be very helpful in anticipating a credit crunch and its effect on the business cycle (Lown, Morgan, and Rohatgi 2000 and Lown and Morgan 2006).

proxies for bad times.[9] The key benefit of this approach is that data on historical banking crises are widely available for a large set of countries going back in time. Given the identification of bad times with banking crises, our empirical strategy is to find indicators which would lead to a build-up of capital buffers ahead of crises, i.e., during the good times. Equally, we assess whether there are variables which signal a release of capital buffers at the onset of banking crises.

The second criterion implies that the variation in the indicator variable should be sufficient to provide a meaningful quantitative guide for the accumulation and release phases. In particular, the signals should be comparable across time and noise-free, avoiding unnecessary reversals of direction from one period to the next. Empirically, this criterion rules out bank-specific indicators. Because of idiosyncratic factors, these tend to fluctuate widely from one year to the next, so that buffers would be built up and released in short succession (Drehmann et al. 2010). Such volatility would wreak havoc in banks' capital planning and would likely encourage banks to treat the countercyclical buffer as the new minimum. Therefore, we do not discuss bank-specific variables in what follows.

The third criterion is self-evident. To the extent possible, regulatory arbitrage should be minimized both within and across borders. And since finance is global, the design should take into account the fact that banks are typically exposed to financial cycles in multiple jurisdictions.

The fourth criterion covers a range of aspects. Rules are especially appealing because of the political economy obstacles that hinder the build-up of buffers during booms. Transparency is needed to support appropriate governance, particularly if strict rules are not feasible and some judgment is required. Cost-effectiveness favors continuity and seamless integration with the rest of the regulatory framework. It suggests that it would be helpful to express the buffer in terms of risk-weighted assets and as an add-on to the regulatory minimum level of capital.[10] Importantly, the scheme would thus

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[9] Drehmann et al. (2010) show that for the United States, for which most of the relevant data are available, banking crises are the only periods when both banking sector losses are high and credit conditions are tightened.

[10] This requirement prevents adjustments that lower the minimum in bad times, as suggested, for example, by Gordy (2009).

retain the cross-sectional differentiation of risk at a given point in time while counterbalancing the tendency of most widely used risk measures to vary procyclically (i.e., to assess risk as low in good times and high in bad times, as illustrated in figure 1).

To ensure robustness and transparency, we considered a representative set of *single* indicator variables as possible anchors for the buffer. As will be shown, single indicators already provide very good guidance, leaving limited scope for incremental improvement through the use of multivariate approaches.[11] Arguably, no rule-based method can fully capture the complex dynamics of financial cycles. Some degree of judgment will always be required.

4. Different Candidates for Anchor Variable

As mentioned above, the anchor variable is best viewed as a proxy for the underlying cyclicality addressed by the instrument. We therefore classify the variables in three categories that correspond to different aspects of the financial cycle: the macroeconomy, banking sector activity, and funding costs. In this section we briefly discuss the pros and cons of these variables, the data used to construct them, and their behavior around episodes of systemic stress.

4.1 The Macroeconomy

Variables that relate to the macroeconomy capture broad trends in the financial and real sectors; as such, they are rough summary measures of aspects of the financial cycle. They also have the advantage of being immune to strategic manipulation by individual institutions. We assess the indicator properties for a number of variables corresponding to real economic activity, financial quantities, and asset prices.[12] These variables are, of course, influenced by the collective

[11] Borio and Drehmann (2009a) and Borio and Lowe (2002) show that combinations of variables have somewhat better signaling properties for systemic financial distress than single indicators.

[12] We also assessed inflation. However, the theoretical link between inflation and systemic risk is unclear and, given its very weak performance, we do not report the results for the sake of brevity.

behavior of banks, but in a reasonably competitive market any single institution would view them as exogenous. In addition, most macroeconomic series are widely available and therefore could be used in many countries.

Real GDP. We consider annual real GDP growth and the (real) output gap. These are the most natural indicators of the aggregate business cycle. That said, as already discussed, the business and the financial cycles, although closely linked, are not fully synchronized.

Real Credit. The cycle is often defined with reference to credit availability. Aggregate real credit growth (annual) could be a natural measure of the credit cycle—in particular, if not only bank credit but all other sources of credit are taken into account. As credit to the private sector tends to grow rapidly during booms and slow down or contract during credit crunches, deviations of credit growth from a trend could be an informative variable. Due to data limitations, we focus on bank credit to the private non-financial sector in our analysis except for the United States, for which we use a broad credit measure.

We exclude public-sector debt from our analysis, as it is countercyclical. It tends to slow down in booms and rise rapidly after stress materializes. Data availability is also an issue, as for many countries information is only available annually. Using annual data for a subset of our sample, we found that the inclusion of public-sector debt severely reduces the performance of credit-related variables, in that they indicate fewer crises and issue more false signals. For brevity, these results are not reported but are available on request.

Credit Relative to GDP. Here we consider two related indicators. The first is the difference between the annual growth of credit (to the private non-financial sector) and the annual growth of output, and the second is the credit-to-GDP gap. Both indicators benchmark credit growth on the growth of overall economic activity, trying to capture whether credit is booming or contracting "excessively" relative to GDP. The difference between the two growth rates performs this comparison at the business-cycle frequency, assuming a constant long-term trend in the credit-to-GDP relationship. By contrast, deviations of the credit-to-GDP ratio from its long-term trend (the "credit-to-GDP gap") are more sensitive to lower-frequency structural changes, such as natural financial deepening.

Monetary Aggregates. In the simplest macro models, money and credit are virtually interchangeable indicators, being the two sides of a simplified bank's balance sheet. However, in both theory and practice, the two do not coincide. Behaviorally, their links with asset prices and asset returns, in particular, are very different. And it is known that the credit-to-deposit ratio has a marked cyclical pattern, notably rising during booms. Banks can fund themselves through non-monetary sources (e.g., wholesale interbank funding) and shift their assets between government securities and credit to the private sector.[13] Empirically, it has also been shown that credit and monetary aggregates series decoupled after the Second World War (see, for example, Schularick and Taylor, forthcoming). Thus, real monetary growth, in our case measured by the annual growth rate in M2, may provide an alternative measure of the financial cycle.

Asset Prices. Asset prices in general, and property prices in particular, tend to show exceptionally strong growth ahead of systemic banking events. They also fall precipitously during periods of financial stress. We therefore consider the annual (real) growth rate of equity prices and property prices. Property prices are a weighted average of residential and commercial property prices, where weights are based on estimates of the relative market shares in each country. We also consider deviations from long-term trends, as equity and property price gaps have proved useful in predicting banking crises (e.g., Borio and Drehmann 2009a).

All gaps are calculated as differences from a *one-sided* Hodrick-Prescott filter. This way the calculation of the trend considers only information that would have been available at the time the buffer is activated, as it excludes the path of the given variable at future dates. The specification of the filter is discussed in the data subsection below.

4.2 Banking Sector Activity

Aggregate measures of bank activity tend to co-move with the business and financial cycles. During periods of high bank profitability, banks tend to increase their intermediation activity through

[13]See Borio and Lowe (2004) for a theoretical and empirical analysis of this issue, including an examination of the comparative leading indicator properties of the two variables.

rapid credit growth and to take on risks. Benign economic conditions are associated with low credit losses and high internal capital resources (retained earnings), as well as cheap and easily available external funding. As a result, the cost of accumulating buffers is comparatively low.

Banking Sector Profits. This is a key indicator of the sector's performance. Earnings are high in good times and reflect losses in times of stress. Admittedly, profit figures can be subject to strategic management by banks, something that may distort their information content. That said, the scope is partly constrained by the scrutiny of analysts, shareholders, and regulators.

Aggregate Gross Losses. This indicator of performance focuses on the cost side (non-performing loans, provisions, etc). The financial cycle is frequently signaled by the fall and rise of realized losses.

4.3 Cost of Funding

This category focuses on the cost to banks of raising funds. By identifying the cycle with fluctuations in the cost of funding, a regulatory rule would incentivize banks to raise funds when these are relatively cheap and allow them to use the buffers in periods of stress, when such funding becomes more expensive.

Banking Sector Credit Spreads (Indices). These are indicators of vulnerabilities in the banking sector, reflecting markets' assessment of the risk of bank failures. By being closely tied to the financial condition of banks, they may be subject to manipulation. Relying on broad indices, where they exist, can mitigate this drawback. In the analysis we consider the average of credit default swaps (CDS) spreads for the largest banks in each country.[14]

Cost of Liquidity. These are indicators of the banking sector's average cost of raising short-term funds. They are closely linked to banks' health and aggregate funding conditions in markets. In normal times interbank markets distribute liquidity seemingly without friction. When severe strains emerge, measures of funding costs,

[14] Gordy (2009) argues in favor of CDS spreads as an anchor variable for a countercyclical buffer.

such as the LIBOR rate, tend to jump. These indicators may therefore be ideal in marking the transition from good to bad times. However, many interbank market rates may be unrepresentative of actual funding conditions. In a crisis, the dispersion in credit quality across banks tends to increase and institutions have a greater incentive to strategically misreport their borrowing costs (Gyntelberg and Wooldridge 2008). Interbank rates, such as LIBOR, which are not based on actual transactions but are the outcome of a survey amongst a panel of banks, could be subject to strategic manipulation. In the analysis we consider three-month LIBOR-OIS spreads, i.e., the difference between the three-month interbank rate minus the rate in three-month overnight index swaps.[15]

Corporate Bond Spreads (Average). This is an indicator of credit quality for the economy at large. During boom phases, spreads are typically lower than average, while they tend to widen suddenly and sharply during periods of stress. Spreads can also be viewed as indicators of the average cost of borrowing in the economy, including by banks. They can thus be used as an anchor for a policy tool that seeks to smooth funding costs. In this analysis, we consider the spread between the yield on BBB corporate bonds and government bonds.

4.4 Data

We analyze thirty-six countries (plus the euro area for some market indicators).[16] The period of analysis starts in 1960 for some countries and series, and at the earliest available date for the rest. All data are quarterly, except for aggregate profits and losses, which are annual.

[15]The spread between government paper and the Eurodollar deposit rate (the so-called TED spread) provides very similar information. For the sake of brevity, these results are not shown here.

[16]Drehmann, Borio, and Tsatsaronis (2011) provide a detailed overview of the data in the sample. The countries included in the analysis are Argentina, Australia, Austria, Belgium, Canada, Chile, China, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, India, Indonesia, Ireland, Italy, Japan, Korea, Lithuania, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Portugal, Singapore, South Africa, Spain, Sweden, Switzerland, Taiwan, Turkey, the United Kingdom, and the United States.

The performance of the anchor variables for the countercyclical capital buffer is assessed against an indicator of banking crises. Admittedly, the dating of banking crises is not uncontroversial (e.g., Boyd, de Nicoló, and Loukianova 2009). We follow the dating of crises in Laeven and Valencia (2008, 2010) as well as in Reinhart and Rogoff (2009). In addition, we use judgment and draw on correspondence with central banks to determine some of the crisis dates. This results in forty-nine different crises. The full list of crisis dates is given in Drehmann, Borio, and Tsatsaronis (2011).

Macroeconomic variables are generally available for all countries and are collected from national authorities, the International Monetary Fund international financial statistics, and the Bank for International Settlements (BIS) database. Property prices are based on BIS statistics and are available only for eighteen countries.

When a variable is expressed as a gap (i.e., as the difference between the current level and the long-term trend),[17] we measure the trend with a one-sided Hodrick-Prescott filter. The backward-looking filter is run recursively for each period and the gap calculated as the difference between the actual value of the variable and the value of the trend at that point. Thus, a GDP trend calculated in, say, 1988:Q1 only takes into account information up to 1988:Q1, and the GDP trend in 2008:Q4 takes into account all information up to 2008:Q4. This is an important practical constraint, as policymakers have to take decisions in real time and rely on data that are available at that point. Before using any trend, we require at least five years of information.[18]

The calculation of the Hodrick-Prescott filter involves a key smoothing parameter λ. Following Hodrick and Prescott (1981), it has become standard to set the smoothing parameter λ to 1,600 for quarterly data. Ravn and Uhlig (2002) show that for series of other frequencies (daily, annual, etc.), it is optimal to set λ equal to

[17]For asset price gaps, the difference between the actual data and the trend at each point in time is normalized by the trend in that period. For the credit-to-GDP gap, we simply take the difference between the actual data and the trend at each point in time.

[18]Ideally, ten years of data would be better (e.g., Borio and Lowe 2002). But given that data are limited for some series in some countries, we chose a five-year window to ensure sufficient observations.

1,600 multiplied by the fourth power of the observation frequency ratio. We set λ for *all* the gaps to 400,000, implying that financial cycles are four times longer than standard business cycles.[19] This seems appropriate, as crises occur on average once in twenty to twenty-five years in our sample. Thus in the main section, λ is set to 400,000 to derive the output, the credit-to-GDP, the property, and the equity gaps. For robustness, we analyzed alternative values of the smoothing parameter and discuss the results in section 6.1.

Data on aggregate profits for banks are hard to obtain. We rely on the OECD banking statistics.[20] Specifically, we use aggregate net provisions, as an indicator of gross losses, and profits before tax. Both are normalized by total assets and are only available on an annual basis. For practical purposes, annual data are unlikely to be sufficient—in particular, when considering the release of the buffer. But the OECD database is the only source for most countries.

Given the heterogeneity in data availability, our analysis for macro and banking sector conditions considers two data sets. The first data set includes all available data and thus uses a different period for the analysis of each variable. The second is a homogenous data set that includes only observations for which all macro variables (including property prices) as well as profit and gross loss indicators are available.

A full analysis of market-based indicators is impossible. Most relevant data start only in the late 1990s and are only available for few countries. Only four crisis episodes fall within the corresponding sample, and three of them are in 2007. Therefore, the performance covers only the most recent crises. For the sake of completeness, we report the analysis on this sample as well. But we do not want to emphasize the results, as they cannot be statistically robust.

[19] This is the same value as in previous comparable work (e.g., Borio and Lowe 2004 and Borio and Drehmann 2009b).

[20] While the OECD data are consistent across countries and broadly available, for some countries (in particular, for the United States and the United Kingdom) they indicate lower profits and losses than other national sources. However, the correlation between different data series in each country is high and typically well above 75 percent. Other data sources are used by Drehmann et al. (2010) for a subset of six countries and yield the same qualitative results as those presented here.

4.5 The Behavior of Candidate Variables around Systemic Crises

As a first step, we look at the performance of different indicator variables around episodes of systemic banking crises. Figures 2–4 summarize the behavior of each variable during a window of sixteen quarters before and after the crisis date (time 0 in the figures). For each variable we use data from as many countries as possible and show the median (solid line) as well as the 25th and 75th percentiles (dashed lines) of the distribution across episodes. The figures provide some insight into how different indicator variables behave during the accumulation and release phases of the capital buffer.

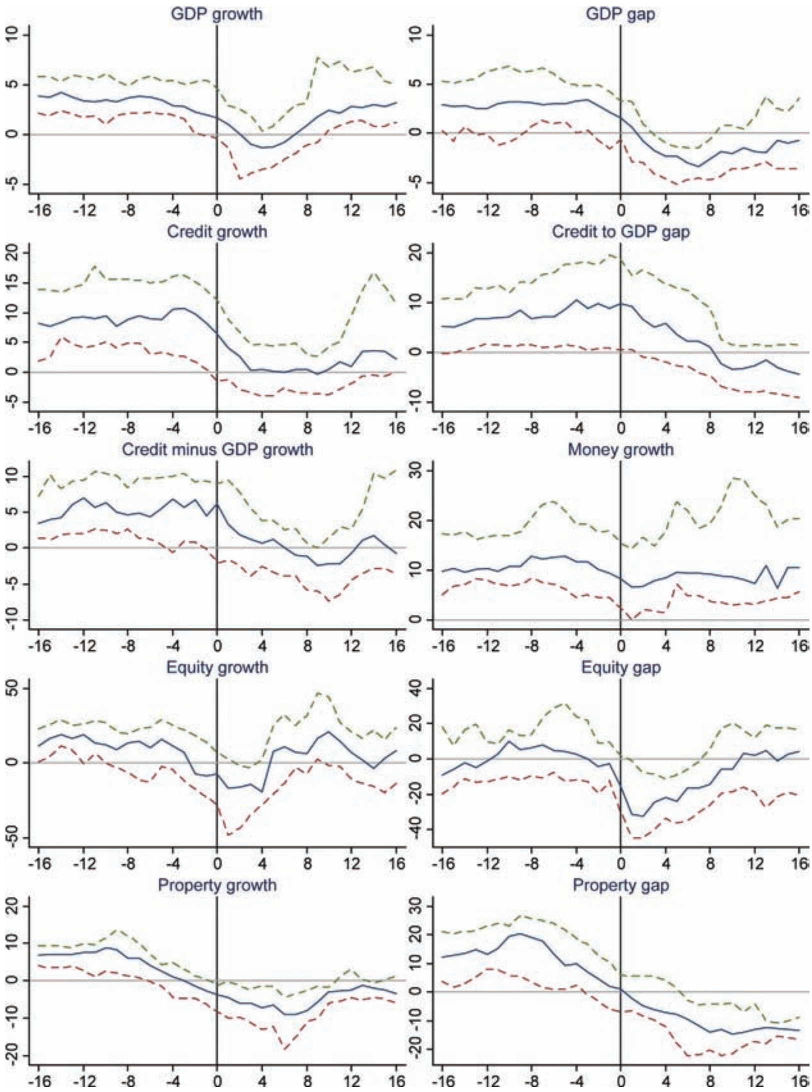
Median real GDP growth is around 4 percent four years prior to a crisis. It then starts to decline, with a slowdown gathering momentum in the year leading up to the crisis. Once the crisis materializes, GDP growth turns negative. After around two years, on average, the economy returns to its pre-crisis growth rate, suggesting that this growth rate is not particularly unusual. Interestingly, the 75th percentile shows that many crises are not preceded by any slowdown in output.[21] In line with real GDP growth, the output gap shows a similar pattern.

Real credit growth, the difference between credit and output growth, and the credit-to-GDP gap, all rise in the lead-up to banking crises. Therefore, they could be useful indicators during the accumulation phase. For the release phase, real credit growth could provide useful information, as it falls significantly around the event. The indicators based on credit in relation to GDP, on the other hand, remain elevated for around one to two years after the crisis. Money growth shows a pattern similar to that of credit growth, even though the rise before and fall after the crisis is less pronounced. Similar to output growth, money growth quickly returns to pre-crisis levels, suggesting that these levels may not be unusual.

As expected, asset, and in particular property, prices tend to grow rapidly ahead of banking crises. This could make them useful indicators for the accumulation phase of the buffer. However, they

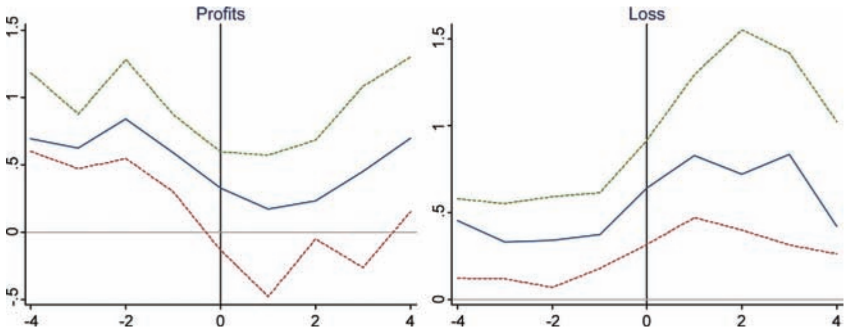
[21] This provides a clear indication that models linking fragilities in the banking sector to weak macroeconomic fundamentals, such as macro stress tests, do not capture the dynamics of many crises (Alfaro and Drehmann 2009).

Figure 2. Macroeconomic Variables around Crises



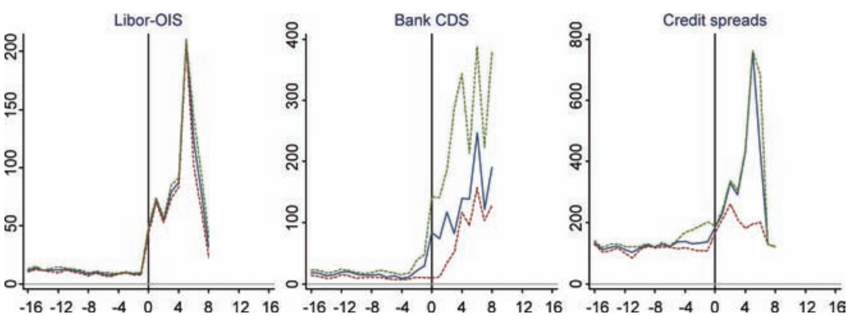
Notes: The horizontal axis depicts plus/minus sixteen quarters around a crisis, which is indicated by the vertical line. The solid line corresponds to the median across all observations in a particular quarter. The upper and lower dashed lines represent the 75th and 25th percentile, respectively.

Figure 3. Banking Sector Conditions around Crises



Notes: The horizontal axis depicts plus/minus four years around a crisis, which is indicated by the vertical line. The solid line corresponds to the median across all observations in a particular quarter before or after the onset of a crisis. The upper and lower dotted lines represent the 75th and 25th percentile, respectively.

Figure 4. Market Indicators around Crises



Notes: The horizontal axis depicts plus/minus sixteen quarters around a crisis, which is indicated by the vertical line. The solid line corresponds to the median across all observations in a particular quarter before or after the onset of a crisis. The upper and lower dotted lines represent the 75th and 25th percentile, respectively. The analysis of market variables ends in 2009:Q4, meaning that only eight quarters of data are available for these series after the beginning of the recent crisis.

tend to fall well before the onset of the crisis. If indicator variables are linked mechanically to capital requirements, this would result in a premature draw-down of the buffers.

Banks' losses increase significantly after crises. Equally, profits drop. However, there is not much variability in the run-up to a crisis, raising questions about the ability of these variables to capture the intensity of the cycle. By contrast, the variables may be useful indicators for the release phase, even though for this purpose the annual frequency is a major drawback.

Market indicators seem to perform exceptionally well as signals for the release of capital. All of them rise significantly around crisis dates. However, before a crisis they seem to be low and stable, thereby not providing clear measures of the intensity of the build-up of systemic risk. That said, given the low number of crises (at most four, in the case of credit spreads) for which market data are available, we need to put a strong caveat on these conclusions.

The discussion suggests that there is possibly no single indicator variable which works equally well for the accumulation and release phases. This is not surprising: it would require a variable that is both a coincident *and* leading indicator of systemic distress—or, in the language of Borio and Drehmann (2009b), an indicator that acts as both a barometer and a thermometer of financial distress. Therefore, we analyze the accumulation and release phases separately, starting with the former.

5. Statistical Analysis

In this section, we assess the performance of the indicators more formally by using a signal-extraction method. After a brief methodological discussion, we analyze the build-up and release phases sequentially.

5.1 Methodology

Following the literature on early-warning indicators for systemic banking crises (e.g., Kaminsky and Reinhart 1999), we use a signal-extraction method to compare the performance of different variables.

We use this method for both the build-up and the release phases, but rely on slightly different specifications in each of the two cases.

Consider the build-up phase first. Let y_t be an indicator variable and $S(y_t)$ a signal which can be 0 ("off") or 1 ("on") depending on whether y is below or above a threshold value k.[22] The signal is "on" if y_t^h exceeds a critical threshold level k, i.e., $S(y_t) = 1$ if $y_t^h > k$. For each indicator variable we assess a range of thresholds (k). A signal of 1 (0) is judged to be correct if a crisis (no crisis) occurs any time within a three-year (twelve-quarter) forward horizon.[23] In the robustness section we will also analyze horizons of one and two years.

We, thus, consider a flexible horizon, as originally suggested by Borio and Lowe (2002). An alternative assumption would be to use a fixed lead-lag relationship, so that a signal at time t would be judged to be correct if a crisis materialized exactly h periods ahead. A range of different forecast horizons could be considered. However, such an approach implicitly confounds the indication that a crisis is imminent with the prediction of its exact timing. We believe this is problematic. The dynamics of banking crises differ considerably across episodes and their exact timing is, almost by definition, unpredictable. What the indicators detect is the general build-up of vulnerabilities in the financial sector that creates the conditions for a crisis. This is the essence of our approach and the reason why we use a window during which a crisis may occur rather than a specific interval of time between signal and event.

The assessment methodology distinguishes between two types of forecast errors: type 1 error, when no signal is issued and a crisis occurs, and type 2 error, when a signal is issued but no crisis occurs. Both error types are summarized by the *noise-to-signal ratio* (NS in the tables), which is the ratio of type 2 errors (as a fraction of non-crisis dates) to 1 minus the fraction of type 1 errors (as a fraction of all crisis dates). The typical trade-off between these two types of

[22]Strictly speaking, indicator variables are of two types: those that are high during boom times (such as profits or credit growth) and those that are low during booms (such as credit spreads). For ease of exposition, we discuss only the former in the text, since the discussion of the latter is symmetric.

[23]If a series starts less than three years before the first crisis date, the series is not considered for the analysis until two years after the onset of this crisis.

errors is that when a variable captures a lot of crises (low type 1 error) it tends to overpredict their number (i.e., issue false signals and exhibit a high type 2 error).

Once in a crisis, it makes no sense to predict another crisis: the indicator has already done its job. We therefore do not consider any signals in the two years after the beginning of a crisis. The two-year window is at the low end of the estimates of the average length of crises. For instance, using the time which GDP requires to recover to its pre-crisis level as a measure of the length of crises, Cecchetti, Kohler, and Upper (2009) find that on average crises last nearly three years. In our sample, the minimum time between two crises in one country is five years. Thus, by assuming that crises last two years, we bias our noise-to-signal ratio upwards, as only type 2 errors can be issued during the quarters immediately following the end of the second year after an episode.

Consider next the release phase. The approach here is broadly similar but recognizes explicitly that crises are sudden events. The release signal has to be issued as a *coincident*, not leading, indicator of distress. Again, the signal for the release is "on" if the indicator variable breaches a particular threshold. For a variable y_t^l which should increase once crises materialize (for example, credit spreads) the signal is $S(y_t) = 1$ if $y_t^l > k$ & $y_{t-1}^l < k$.[24] To account for the uncertainty in the precise dating of crises, we judge a signal of 1 (0) to be correct if a crisis occurs (does not occur) during a window of three quarters starting with the quarter prior to the date in which the signal is issued. Again, we assess a range of thresholds for each indicator variable and compute type 1 errors, type 2 errors, and the noise-to-signal ratio.

The literature assesses early-warning indicators on the basis of their noise-to-signal ratio (e.g., Kaminsky and Reinhart 1999). However, Demirgüç-Kunt and Detragiache (1999) suggest that this is not ideal from a policy perspective, as policymakers may assign more weight to the risk of missing crises (type 1 error) than to the risk of calling those that do not occur (type 2 error), as the costs of the two

[24]The procedure is symmetric for variables the value of which tends to drop during a crisis (for example, credit growth).

differ.[25] Jordà and Taylor (2011) suggest an alternative approach to capture the trade-off between type 1 and type 2 errors. They construct the correct classification frontier.[26]

As the preferences of policymakers are unobservable, Borio and Drehmann (2009a) suggest minimizing the noise-to-signal ratio subject to at least two-thirds of the crises being correctly predicted. They show that the more concerned a policymaker is about missing crises (type 1 error), the lower are the critical thresholds to be crossed before signaling crises and the noisier the indicators become. At the other end of the spectrum, minimizing the noise-to-signal ratio regardless of the number of crisis predictions generally results in an unacceptably low percentage of crises predicted. On balance, they find that minimizing the noise-to-signal ratio subject to at least two-thirds of the crises being correctly predicted appears to provide a good compromise. We follow this criterion, even though the key messages of the paper would remain unchanged if we had chosen other cut-off levels for the minimum required fraction of correctly predicted crises (e.g., 50 percent or 75 percent). In tables 2–9 (discussed below) we use boldface entries in the columns labeled "Predicted" to denote threshold values that lead to a crisis prediction rate of at least 66 percent. The boldface entries in the columns labeled NS indicate the lowest noise-to-signal ratio for those threshold values that satisfy the condition of a minimum 66 percent prediction rate. Tables 2–5 in the main text only show the best performance of different indicators, i.e., they show the threshold for each indicator which achieves the lowest noise-to-signal ratio whilst capturing at least 66 percent of the crises, or, if this requirement is not fulfilled, simply the threshold with the lowest noise-to-signal ratio. The extended analysis is presented in tables 6–9 in the appendix.

[25]This problem was also highlighted by Bussière and Fratzscher (2008) in the context of logit models. See also Alessi and Detken (2011) for an application and extension.

[26]Similar to a production possibilities frontier, the correct classification frontier plots the relationship between correctly predicting crises and type 2 errors. Given a particular utility function, policymakers could pick the threshold that maximizes their utility. Jordà and Taylor (2011) suggest that, independently of policymakers' preferences, the area below this curve represents a simple non-parametric statistic for the usefulness of an indicator.

Table 2. The Best Performance of Indicator Variables for the Build-Up

Variable	All				Homogenous Data			
	#Cr	TH	Pred.	NS	#Cr	TH	Pred.	NS
Macroeconomic Variables								
GDP Growth	40	3.5	**90**	**60**	18	3.5	**89**	**39**
GDP Gap	37	3	**76**	**49**	18	3	**78**	**46**
Credit Growth	45	12	**67**	**33**	18	8.5	**67**	**28**
Credit Growth – GDP Growth	39	8	**69**	**23**	18	5	**67**	**37**
Credit-to-GDP Gap	36	10	**67**	**16**	18	12	**67**	**15**
M2 Growth	40	14	**70**	**53**	18	12	**67**	**16**
Property Growth	25	7	**68**	**30**	18	3	**72**	**65**
Property Gap	22	10	**77**	**33**	18	10	**78**	**40**
Equity Growth	28	23	**79**	**34**	18	21	**89**	**32**
Equity Gap	26	10	**69**	**60**	18	20	**67**	**50**
Banking Sector Conditions								
Profits	28	0.70	**71**	**79**	18	0.60	**72**	**92**
Loss	28	0.40	**68**	**77**	18	0.40	**72**	**93**
Market Indicators								
Bank CDS	4	15	**75**	**44**				
LIBOR-OIS	3	10	**67**	**60**				
Credit Spreads	4	130	**75**	**79**				

Notes: #Cr: number of crises that are included in the analysis. TH: threshold; for macroeconomic variables and banking sector conditions in percent; for market indicators in basis points. Pred.: percentage of crises predicted correctly. NS: noise-to-signal ratio; fraction of type 2 errors (a signal is issued and no crisis occurs) divided by one minus the fraction of type 1 errors (no signal is issued and a crisis occurs). For all variables (except profits and market indicators), a signal equal to 1 is issued when the conditioning variable exceeds (is smaller than) the threshold. Otherwise, the signal is equal to 0. A signal of 1 (0) is judged to be correct if a crisis (no crisis) occurs any time within a three-year horizon. Bold figures indicate that more than 66 percent of crises are captured. For a more detailed analysis, see table 6 in the appendix.

5.2 *The Build-Up Phase*

Table 2 shows the best performance of the different indicator variables for the build-up phase. The results of the full analysis are provided in table 6 in the appendix. For macroeconomic variables and banking sector conditions, the tables show the results for the full and restricted samples, with the latter including only the period for which we have a complete set of variables for all countries.[27] Initially we focus only on the results when all data are used. We first highlight the best-performing indicator and then discuss the remaining ones, ordering them roughly from the worst to the best.

Looking at table 2, we see that the credit-to-GDP gap achieves the lowest noise-to-signal ratio, 16 percent, while still capturing at least 66 percent of the crises in the sample.

The worst performers are indicators of banking sector conditions. As already suggested by the descriptive figures, they cannot signal the build-up of systemic risk well. When at least 66 percent of the crises are captured, the signals are quite unreliable (noise-to-signal ratios well above 70 percent).

Noise-to-signal ratios for market-based indicators are also very high, varying between 44 percent and 80 percent. In contrast to other variables, the results for these indicators highlight a striking pattern, albeit subject to the strong caveat related to the very limited number of crises: the indicators' performance improves dramatically from predicting no crises to capturing all episodes with only small changes in the thresholds. For instance, average CDS spreads across the whole sample are around 50 basis points, peaking well above 100 basis points during the recent crisis. Yet all the crises in the sample (which are only four) would have been correctly signaled by spreads below 20 basis points and none would have been captured by a threshold of 5 basis points. In essence, this means that during normal and boom times, these variables do not seem to fluctuate much. Hence, these series are unable to provide useful signals about the intensity of the build-up of systemic risk.

Output variables, money growth, and the equity gap also perform poorly, albeit slightly better than banking sector conditions and market-based indicators. The lowest noise-to-signal ratios lie between 40 and 60 percent. The results for GDP growth and the output gap argue against linking countercyclical capital buffers to output if the macroprudential objective is defined narrowly in terms of protecting the banking system against the build-up of systemic stress.

[27] As additional robustness checks, we analyzed data samples that include only countries that are members of the Basel Committee, or only data from 1980 onwards. We also analyzed a broader range of thresholds than those shown in the tables. These alternatives do not affect the main messages of the analysis. Results are available on request.

The remaining variables (credit growth, the difference between credit and GDP growth, equity price growth, and property price growth and its gap) seem to be the second-best class of indicators after the credit-to-GDP gap. This is not surprising, as these variables capture key aspects of the build-up of systemic risk ahead of many crises, namely an unsustainable credit expansion alongside booming asset prices.

The broad picture is unchanged when the homogenous data set is used. The key difference is that money growth performs nearly as well as the credit-to-GDP gap in this sample.[28] But in contrast to the case of the credit-to-GDP gap, this result is not stable. When we consider the entire data set (and, hence, all crisis episodes) and select thresholds that allow the indicators to capture more than two-thirds of crises, the noise-to-signal ratio increases unacceptably to above 50 percent.

The results provide valuable information about the performance of different variables. However, we need to keep two caveats in mind.

First, we have assessed the signaling properties of *domestic* indicators of the financial cycle. But systemic problems may occur because of banks' foreign exposures. The cases of German and Swiss banks in the recent crisis are obvious examples. Borio and Drehmann (2009a) show how this signaling problem can be partially addressed by incorporating foreign claims in the assessment of banks' vulnerabilities. We explore this in more detail in section 6.2.

Second, a statistical type 2 error is not necessarily a type 2 error from a policy perspective. Often the conditioning variable starts indicating the build-up of vulnerabilities earlier than three years before a crisis. In the statistical analysis, such a signal is counted as false even though it provides the right information, but simply "too early." There are also instances of severe banking strains without a crisis being formally recorded (possibly because of mitigating policy action to diffuse pressure on the banking system). Therefore, an indicator may issue false signals in the statistical sense, even though additional capital buffers would have been highly valuable to cushion the impact of the stress on the banking system.

[28]The performance of property prices is also sensitive to the sample. This partly reflects the requirement that 66 percent of the crises should be predicted. A one-to-one comparison for each threshold indicates a slightly weaker predictive power for each threshold with a similar level of type 2 errors, resulting in somewhat higher noise-to-signal ratios.

Even with this broader view of false signals, it is clear that no variable provides perfect signals. This means that, in practice, pure rule-based schemes may not be desirable. Some form of discretion may prove inevitable.

5.3 The Release Phase

Although the credit-to-GDP gap is the best-performing indicator for the build-up phase, figure 2 indicates that it declines only slowly once crises materialize. This is also borne out by the statistical tests shown in table 3 (the results of the full analysis are provided in table 7 in the appendix). As before, bold values for "Predicted" highlight thresholds for which a release signal is issued correctly for at least 66 percent of the crises. The bold noise-to-signal ratio indicates the lowest noise-to-signal ratio for all threshold values that satisfy this condition.

None of the macro variables and of the indicators of banking sector conditions satisfy the required degree of predictive power to make them robust anchor variables for the release phase; i.e., none of these variables signal more than 66 percent of the crises. The best indicator is a drop of credit growth below 8 percent. This happens at the onset of more than 40 percent of crises, and such a signal provides very few false alarms (the noise-to-signal ratio is around 10 percent).

Market-based indicators do signal the onset of crises but with considerable noise (in terms of false signals). Take credit spreads, for which most data are available. They breach the 200-basis-point barrier in 75 percent of all crisis episodes. However, the noise-to-signal ratio is close to unity, rendering the overall signal unreliable. This partly reflects the high correlation of spreads across countries. The 200-basis-point threshold was breached in Canada and Australia around 2007:Q3, even though neither country experienced a crisis. Credit spreads also rose quickly during the dot-com bust, a period not associated with banking crises. That said, all these results are derived from a sample that is too small to support robust conclusions.

Overall, the results indicate that policymakers may need to rely much more on discretion for the release phase than for the build-up phase. No single variable provides reliable and robust signals for this stage.

Table 3. The Best Performance of Indicator Variables for the Release

	All				Homogenous Data			
Variable	**#Cr**	**TH**	**Pred.**	**NS**	**#Cr**	**TH**	**Pred.**	**NS**
Macroeconomic Variables								
GDP Growth	40	5	25	25	18	5	6	87
GDP Gap	37	3	27	12	18	3	28	11
Credit Growth	45	8	43	12	18	8	44	9
Credit Growth – GDP Growth	39	6	26	22	18	6	28	18
Credit-to-GDP Gap	36	10	14	11	18	10	22	8
M2 Growth	40	12	20	25	18	12	17	20
Property Growth	25	2	12	42	18	2	11	35
Property Gap	22	4	32	6	18	4	39	3
Equity Growth	28	23	21	35	18	23	22	30
Equity Gap	26	15	19	21	18	15	22	20
Banking Sector Conditions								
Profits	28	0.60	31	24	18	0.60	30	30
Loss	28	0.70	32	229	18	0.70	33	171
Market Indicators								
Bank CDS	4	10	50	156				
LIBOR-OIS	3	50	**67**	**90**				
Credit Spreads	4	210	**75**	**105**				

Notes: #Cr: number of crises that are included in the analysis. TH: threshold; for macroeconomic variables and banking sector conditions in percent; for market indicators in basis points. Pred.: percentage of crises predicted correctly. NS: noise-to-signal ratio; fraction of type 2 errors (a signal is issued and no crisis occurs) divided by one minus the fraction of type 1 errors (no signal is issued and a crisis occurs). For all variables (except profits and market indicators), a signal equal to 1 is issued when the conditioning variable exceeds (is smaller than) the threshold. Otherwise, the signal is equal to 0. A signal of 1 (0) is judged to be correct if a crisis (no crisis) occurs any time within a three-year horizon. Bold figures indicate that more than 66 percent of crises are captured. For a more detailed analysis, see table 7 in the appendix.

6. Robustness

In this section we evaluate the robustness of our results. First, we assess the signaling properties of the credit-to-GDP gap calculated by reference to alternative specifications of the trend. We consider different specifications for the one-sided HP filter and we discuss a more conventional two-sided filter. Second, we explore different signaling horizons. Third, we explore how our analysis linking domestic indicator variables with banking crises gels with a financial system that is global and exposes banks to shocks from abroad.

6.1 The Signaling Properties of Different Credit-to-GDP Gaps

In this section we assess the impact of two unconventional choices we made in the calculation of the credit-to-GDP trend. The first relates to the choice of a one-sided trend (i.e., a backward-looking Hodrick-Prescott filter) and the second to that of the smoothing parameter λ.

Edge and Meisenzahl (2011) perform an analysis for the credit-to-GDP ratio using real-time and revised data for the United States and conclude that revisions can lead to substantial changes to the estimated gap.[29] They evaluate the impact of revisions to the credit-to-GDP gap from two sources: data revisions and the unfolding of history. As regards the former, they compare the impact of revisions to the credit and GDP series on the original estimate of trend and find that they contribute only to a small extent to the revised gap estimates. As regards the latter, they compare the one-sided with a two-sided filter, which encompasses information *about the future* relative to the point in time when decisions are taken. They find that the one-sided trend differs substantially from the two-sided one. Based on this, they conclude that the credit-to-GDP gap is an unreliable guide for countercyclical capital buffers.

The message of Edge and Meisenzahl (2011) is, in our view, misleading. They focus their attention on the difference between the gap calculated using the one-sided filter ending in a given quarter to that calculated using information from subsequent quarters. The mismeasurement they identify is obviously *impossible* for the policymaker to correct in real time, *since the data needed cannot be available*. Moreover, and most importantly for the purpose of this paper, they do not assess the indicator performance of the credit-to-GDP gap calculated on the basis of future information. Only if the indicator performance is seriously hampered by the calculation of the trend could their conclusion be a reason for concern. Even then, from an applied policy perspective, a trend calculation that requires future information is problematic.

[29] A similar analysis was conducted for the U.S. GDP gap by Orphanides and van Norden (2002).

Table 4. The Best Performance of Different Credit-to-GDP Gaps

	All				Homogenous Data			
Horizon	**#Cr**	**TH**	**Pred.**	**NS**	**#Cr**	**TH**	**Pred.**	**NS**
Real Time, HP $\lambda = 400{,}000$ (Standard)	36	10	**67**	**16**	18	12	**67**	**15**
Two-Sided Filter (Past and Future Known), HP $\lambda = 400{,}000$	36	6	**72**	**17**	18	8	**67**	**10**
Real Time, HP $\lambda = 1{,}600$	36	2.5	**69**	**30**	18	2	**67**	**46**
Real Time, Linear Trend	36	8	**67**	**22**	18	10	**67**	**23**

Notes: #Cr: number of crises that are included in the analysis. TH: threshold; in percent. Pred.: percentage of crises predicted correctly. NS: noise-to-signal ratio; fraction of type 2 errors (a signal is issued and no crisis occurs) divided by one minus the fraction of type 1 errors (no signal is issued and a crisis occurs). For all variables, a signal equal to 1 is issued when the conditioning variable exceeds the threshold. Otherwise, the signal is equal to 0. A signal of 1 (0) is judged to be correct if a crisis (no crisis) occurs any time within a three-year horizon. Bold figures indicate that more than 66 percent of crises are captured. Real-time trends use information available up to each point in time in which the signal is issued. The two-sided filter uses all available information in the data set. For a more detailed analysis, see table 8 in the appendix.

The first and second rows in table 4 (see table 8 in the appendix for a more detailed analysis) compare the performance of the gap based on the one-sided (labeled "standard") and two-sided Hodrick-Prescott (HP) filters (the results of the full analysis are provided in table 8 in the appendix). Both trends are estimated using a smoothing factor λ of 400,000. The table shows that knowing the future does not actually help in this case. For the homogenous data set, the statistical performance is marginally better. But it is actually worse if all data are considered.

The second robustness issue refers to the choice of λ. First, in line with standard business-cycle analysis, we construct credit-to-GDP gaps using a one-sided HP filter with a smoothing factor λ of 1,600.[30] As discussed above, this implies that credit cycles would have the

[30] As a robustness check, we also analyzed output and asset price gaps using a smoothing factor λ of 1,600. This does not improve the performance of these variables in comparison to the results shown in table 6. Drehmann et al. (2010) also assess credit-to-GDP gaps based on $\lambda = 25{,}000$ and $\lambda = 125{,}000$, which

same length as business cycles. Second, we use a simple linear time trend, based on fifteen years of rolling regressions.[31]

Table 4 (and the full results in table 8 in the appendix) shows that a linear trend performs well, even though it is slightly noisier than the credit-to-GDP gap based on an HP filter with $\lambda = 400{,}000$. The table illustrates that a gap calculated using $\lambda = 1{,}600$ (i.e., assuming that credit cycles and business cycles are of the same length) performs poorly. We take this result as another indication that the financial and business cycles are not the same.

6.2 *The Forecast Horizon*

As discussed in the methodology section 5.1, in the benchmark specification we adopt a flexible forecast horizon, so that a crisis signal is judged to be correct (false) if a crisis (no crisis) occurs *any time* within a three-year interval. As already argued, in our view this is the right approach, as indicators only highlight the build-up of vulnerabilities rather than provide clear-cut signals of the precise future timing of crises. Even so, here we explore different forecast horizons. Table 5 shows the key results (the results of the full analysis are provided in table 9 in the appendix) when a crisis signal is judged to be correct if a crisis occurs in the next, the second, *or* the third year ahead. In addition, we analyze two-year horizons for years 1 and 2, and 2 and 3, respectively. For brevity we only show the results for the credit-to-GDP gap, which remains the best single indicator for all different horizons considered.[32]

When the forecast horizon is limited to a single year, the performance deteriorates relative to our standard approach, but not by too much. This is not surprising, as figure 2 reveals that the credit-to-GDP gap is highly persistent. Take a threshold of 4 percentage points (see table 9 in the appendix). In the standard approach with the homogenous data set, 89 percent of the crises are captured and the

assumes that credit cycles are two or three years longer than business cycles. The statistical performance of the credit gap with $\lambda = 400{,}000$ remains best.

[31] We also used five- or ten-year windows to construct the trend. Predictably, decreasing the number of years used to construct the linear trend worsens the performance of the gap as indicator. In particular, during periods of sustained credit growth, the trend catches up too quickly, so that gaps start declining more markedly ahead of crises.

[32] Results for other variables are available on request.

Table 5. The Best Performance of Different Signaling Horizons

	All				Homogenous Data			
Horizon	**#Cr**	**TH**	**Pred.**	**NS**	**#Cr**	**TH**	**Pred.**	**NS**
Year 1 & 2 & 3 (Standard)	36	10	**67**	**16**	18	12	**67**	**15**
Year 1	36	6	**67**	**36**	18	11	**67**	**24**
Year 2	36	6	**67**	**34**	18	9	**67**	**28**
Year 3	36	5	**69**	**36**	18	5	**78**	**40**
Year 1 & 2	36	8	**67**	**25**	18	11	**67**	**21**
Year 2 & 3	36	7	**67**	**27**	18	10	**72**	**19**

Notes: #Cr: number of crises that are included in the analysis. TH: threshold; in percent. Pred.: percentage of crises predicted correctly. NS: noise-to-signal ratio; fraction of type 2 errors (a signal is issued and no crisis occurs) divided by one minus the fraction of type 1 errors (no signal is issued and a crisis occurs). A signal equal to 1 is issued when the credit-to-GDP gap exceeds the threshold. Otherwise, the signal is equal to 0. A signal of 1 at time t is judged to be correct (false) if a crisis (no crisis) occurs over the following signaling horizons: (i) "year 1 to 3": quarters $t+1$ to $t+12$, (ii) "year 1": quarters $t+1$ to $t+4$, (iii) "year 2": quarters $t+5$ to $t+8$, (iv) "year 3": quarters $t+9$ to $t+12$, (v) "year 1 and 2": quarters $t+1$ to $t+8$, and (vi) "year 2 and 3": quarters $t+5$ to $t+12$. Bold figures indicate that more than 66 percent of crises are captured. For a more detailed analysis, see table 9 in the appendix.

type 2 error is 36 percent. When only individual years are considered, the predictive power drops to 83 percent and the noise increases (the worst case is for year 1, where type 2 errors are equal to 41 percent). These effects are somewhat more pronounced when all data are considered.

Interestingly, in comparison to the standard approach, the predictive power is only marginally reduced when a two-year horizon is used. And in this case it is virtually the same when the signaling horizon covers years 1 and 2 or 2 and 3. From an operational perspective, the strong performance of the credit-to-GDP gap in years 2 and 3 before crises is important, as capital planning by the banks requires that they know their regulatory capital requirement at least one year before they become effective (Basel Committee on Banking Supervision 2010). Hence, if countercyclical capital requirements were raised following a signal, capital would be available only with a one-year lag.

6.3 The International Dimension

Finance is increasingly international. The outstanding stock of banks' foreign claims tripled between 2000 and 2007 from $11 trillion to over $30 trillion. The ten largest banks operate on average in around eighty countries in the world. Cross-border borrowing and lending has implications for the specification of the anchor variable. For one, domestic borrowers' improved access to international sources of credit means that domestic credit figures may understate the extent of their leverage and vulnerability to shocks. In addition, banks located in a given country may be exposed to risks in other countries—risks that are not captured by a domestically focused indicator. Crises can occur because of losses on foreign exposures. In this section we discuss how the credit-to-GDP ratio can be adjusted to deal with these issues.

The first complication relates to the coverage of the credit variable proxying the financial cycle *in a given country*. It covers lending to households and business residents in a given jurisdiction. The reliability of this proxy should be, as a first approximation, independent of the source of credit (domestic, international, bank originated, or market based). Hence, the credit aggregate should be as broad as possible. In our analysis, however, the credit series generally include only credit granted by banks *located* in the given country; i.e., they exclude direct cross-border lending to domestic households and businesses from non-residents. This is typically what the credit and banking statistics cover. We have conducted a preliminary analysis of the effect of including a more comprehensive measure of credit to domestic borrowers, drawing on the BIS international banking statistics.[33] The preliminary results are consistent with those reported in this paper. Large credit-to-GDP gaps provide a reliable signal ahead of systemic banking crises.

The second complication relates to the possibility of exposures of the banking system in a given country to financial cycles in the rest

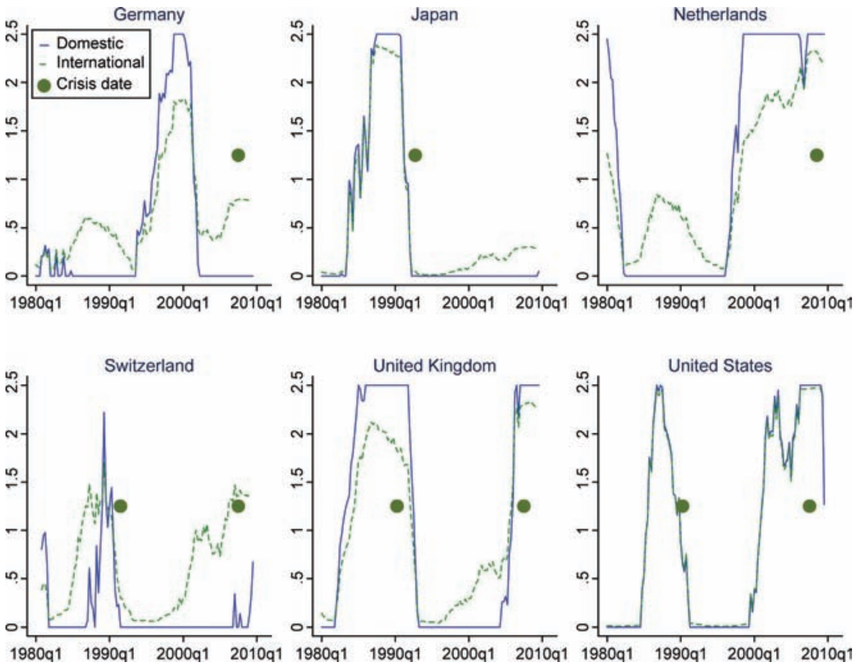
[33] A number of data issues complicate this analysis. For instance, data availability on non-bank sources of finance is rather poor in some countries, and differences in the treatment of exchange rate changes in the reported series can introduce significant noise.

of the world. This means that, in principle, the signaling property of the credit-to-GDP indicator should be evaluated on the basis of the composition of *global* exposures of domestic banks. While these are known to supervisors, in our analysis we can only use rough aggregate proxies. To do so, we follow a three-step procedure similar to that in Borio and Drehmann (2009b). We first need to convert the indicator into something that can be combined across economies. We do this by constructing a (hypothetical) capital surcharge that varies with the value of the credit-to-GDP gap. The mapping we selected is one in which the surcharge increases linearly between zero and 2.5 percent as the value of the indicator increases between a minimum level (equal to 2 percentage points) and a maximum level (equal to 10 percentage points). So the surcharge is zero if the credit-to-GDP gap is less than 2 percentage points, and it is equal to 2.5 percent if the gap is greater than or equal to 10 percentage points. This calibration is in line with the proposals by the Basel Committee on Banking Supervision (2010). In the second step, we calculate for each country the share of total assets of banks headquartered in that country that is accounted for by claims vis-à-vis other countries. This is done by drawing on the BIS international banking statistics.[34] In the final step, we use these shares to construct a weighted average of the capital charges that would apply to exposures in each country in which the banks have a claim.

Figure 5 compares for six countries (Germany, Japan, the Netherlands, Switzerland, the United Kingdom, and the United States) the capital surcharge calculated based solely on domestic exposures with that based on the global exposures of the representative bank. The dots denote banking crises. The results are encouraging. Capital buffers build up to their maximum ahead of major systemic crises. Moreover, the indicator that includes proxies for banks' international exposures captures better the problems faced by the German and Swiss banking sectors, which incurred losses largely on lending to non-residents, notably to U.S. borrowers.

[34]The statistics refer to aggregate claims and not individual bank claims. They are reported on a consolidated basis. For a description of structure and coverage of the statistics, see McGuire and Wooldridge (2005).

Figure 5. International Exposures and Countercyclical Capital Charges



Notes: The domestic buffer reflects the credit-to-GDP gap of the specific country and would reflect the total charge for banks located there if they did not have any international exposures. The international buffer is the buffer of a hypothetical bank whose portfolio of domestic and cross-border credit corresponds to that of the banking system in the given jurisdiction. Country exposure weights are based on the BIS international banking statistics and correspond to claims as of 2006:Q4.

7. Conclusion

The objective of prudential countercyclical bank capital standards is to encourage banks to increase their defenses against systemwide vulnerabilities by building up buffers in good times so that they can draw them down in bad times. Our analysis examined the suitability of different variables to act as anchors for the build-up and release phases of the buffers.

The analysis shows that the best variables to signal the pace and size of the *build-up* of the buffers differ from those that provide the best signals for their *release*. Credit, measured by the deviation of the credit-to-GDP ratio from its trend, emerges as the best variable for the build-up phase, as it has the strongest leading indicator properties for financial system distress. A side benefit of using this variable as the anchor is that it could help to restrain the credit boom and hence risk taking to some extent.

How to guide the pace and intensity of the release of the buffer is less clear. In general, a prompt and sizable release is desirable, as a gradual release could reduce the buffer's effectiveness. A combination of a measure of aggregate losses with indicators of tightening of credit conditions would provide, conceptually, the proper signal for the beginning of the period of systemwide stress, thus triggering the release. Among the single indicators we evaluated, credit spreads are the most promising, albeit over the shorter period over which we were able to assess them. But the performance of these variables for the release is not as good as that of the credit-to-GDP gap for the build-up.

Our analysis also makes clear that any operational framework would need to incorporate an element of judgment, especially in the release phase. As in other fields of economic policy, rules provide invaluable discipline but may not work well in all circumstances. Given the relatively early stage in the economic analysis of the interactions between the real and financial sectors of the economy, it would be premature to claim that any rule can be sufficiently robust across countries and time. Moreover, the political economy of the design and application of macroprudential instruments, such as the countercyclical capital buffer, is a field in which much more analysis is needed.

A final word of caution is in order. Are our empirical results subject to the usual Lucas or Goodhart critiques? In other words, *if the scheme proved successful*, would the leading indicator properties of the credit-to-GDP variable disappear? The answer is "yes," by definition, if the criterion of success was avoiding major distress among banks. As credit exceeds the critical threshold, banks would build up buffers to withstand the bust. Moreover, if, in addition, the scheme acted as a brake on risk taking during the boom, the bust would be less likely in the first place. The answer is less clear if the criterion was the more ambitious one of avoiding disruptive financial busts: busts could occur even if *banks* remained reasonably resilient. In either situation, however, the loss of predictive content per se would be *no reason* to abandon the scheme.

Appendix

Table 6. The Performance of Macroeconomic Variables for the Build-Up

Threshold	All Data				Homogenous Data			
	T 1	T 2	Pred.	NS	T 1	T 2	Pred.	NS
GDP Growth (40/18)								
3	8	61	**93**	66	11	42	**89**	48
3.5	10	54	**90**	**60**	11	35	**89**	**39**
4	23	48	**78**	62	33	28	**67**	42
4.5	33	42	**68**	62	50	21	50	41
5	35	36	65	56	56	15	44	35
GDP Gap (37/18)								
1	16	53	**84**	63	11	54	**89**	61
2	16	44	**84**	53	11	44	**89**	50
3	24	37	**76**	**49**	22	36	**78**	**46**
4	35	30	65	47	44	29	56	52
Credit Growth (45/18)								
8	16	40	**84**	47	22	23	**78**	29
8.5	20	37	**80**	46	33	19	**67**	**28**
9	22	34	**78**	44	39	16	61	26
11	29	26	**71**	36	44	8	56	15
12	33	22	**67**	**33**	50	6	50	12
13	38	19	62	30	56	5	44	12
Credit Growth – GDP Growth (39/18)								
4	10	38	**90**	42	11	32	**89**	36
5	21	30	**79**	38	33	24	**67**	**37**
6	23	24	**77**	32	39	17	61	28
8	31	16	**69**	**23**	44	9	56	16
9	38	13	62	21	44	6	56	11
Credit-to-GDP Gap (36/18)								
2	11	38	**89**	43	6	45	**94**	48
4	17	29	**83**	35	11	36	**89**	41
6	25	21	**75**	28	17	27	**83**	33
8	31	16	**69**	23	22	20	**78**	26
10	33	11	**67**	**16**	22	14	**78**	18
12	47	8	53	14	33	10	**67**	**15**
14	58	5	42	13	50	7	50	15
M2 Growth (40/18)								
8	10	64	**90**	71	17	30	**83**	36
10	18	53	**83**	65	22	17	**78**	22
12	23	44	**78**	57	33	11	**67**	**16**
14	30	37	**70**	**53**	44	8	56	14
16	40	31	60	52	67	6	33	18

(continued)

Table 6. (Continued)

Threshold	All Data				Homogenous Data			
	T 1	T 2	Pred.	NS	T 1	T 2	Pred.	NS
Property Growth (25/18)								
2	16	51	**84**	61	22	53	**78**	68
3	20	45	**80**	56	28	47	**72**	**65**
4	28	39	**72**	54	39	41	61	66
6	28	26	**72**	37	39	29	61	47
7	32	20	**68**	**30**	39	21	61	34
8	44	17	56	30	56	17	44	38
Property Gap (22/18)								
6	14	38	**86**	43	17	43	**83**	52
8	18	31	**82**	38	22	38	**78**	49
10	23	26	**77**	**33**	22	31	**78**	**40**
12	36	22	64	35	39	27	61	43
Equity Growth (28/18)								
19	14	32	**86**	37	11	31	**89**	35
21	14	30	**86**	34	11	28	**89**	**32**
23	21	27	**79**	**34**	22	26	**78**	33
25	39	25	61	42	44	24	56	44
Equity Gap (26/18)								
5	19	49	**81**	61	11	54	**89**	61
10	31	42	**69**	**60**	22	46	**78**	59
15	35	35	65	53	28	40	**72**	55
20	42	29	58	50	33	33	**67**	**50**
25	58	24	42	58	56	28	44	64
Profits (28/18)								
0.40	4	82	**96**	85	6	84	**94**	89
0.50	11	76	**89**	85	17	78	**83**	94
0.60	21	67	**79**	86	28	66	**72**	**92**
0.70	29	57	**71**	**79**	39	58	61	95
0.80	46	47	54	87	56	50	44	113
0.90	57	38	43	89	56	41	44	93
Loss (28/18)								
0.70	4	80	**96**	83	6	89	**94**	94
0.60	4	73	**96**	76	6	85	**94**	90
0.50	11	63	**89**	71	11	79	**89**	88
0.40	32	52	**68**	**77**	28	67	**72**	**93**
0.30	50	39	50	78	39	54	61	89
0.20	61	24	39	61	50	38	50	76

(continued)

Table 6. (Continued)

Threshold	All Data				Homogenous Data			
	T 1	**T 2**	**Pred.**	**NS**	**T 1**	**T 2**	**Pred.**	**NS**
Bank CDS (4/0)								
20	0	49	**100**	49				
15	25	33	**75**	**44**				
10	50	8	50	16				
5	100	0	0	0				
LIBOR-OIS (3/0)								
14	33	73	**67**	109				
12	33	55	**67**	82				
10	33	40	**67**	**60**				
8	67	37	33	111				
Credit Spreads (4/0)								
140	25	62	**75**	82				
130	25	59	**75**	**79**				
120	50	54	50	109				
110	50	49	50	97				

Notes: Threshold: for macroeconomic variables and banking sector conditions in percent; for market indicators in basis points. T1: type 1 error, no signal is issued and a crisis occurs. T2: type 2 error, a signal is issued and no crisis occurs. Pred.: percentage of crises predicted correctly. Bold figures in this column indicate that more than 66 percent of crises are captured. NS: noise-to-signal ratio; fraction of type 2 errors divided by one minus the fraction of type 1 errors. Bold figures in this column indicate the lowest noise-to-signal ratio given that more than 66 percent of crises are captured. For all variables (except profits and market indicators), a signal equal to 1 is issued when the conditioning variable exceeds (is smaller than) the threshold. Otherwise, the signal is equal to 0. A signal of 1 (0) is judged to be correct if a crisis (no crisis) occurs any time within a three-year horizon. The numbers in parentheses next to the name of the variable correspond to the number of crises that are included in the analysis using the sample that includes the available data for that variable (left-hand-side number) and the homogenous sample (right-hand-side number), respectively.

Table 7. The Performance of Indicator Variables for the Release

Threshold	All Data				Homogenous Data			
	T 1	**T 2**	**Pred.**	**NS**	**T 1**	**T 2**	**Pred.**	**NS**
GDP Growth (40/18)								
3	78	7	23	29	94	8	6	140
3.5	80	7	20	34	100	7	0	—
4	73	7	28	26	94	7	6	130
4.5	78	7	23	30	94	6	6	114
5	75	6	25	25	94	5	6	87
GDP Gap (37/18)								
1	78	4	22	17	67	3	33	9
2	73	4	27	13	67	3	33	8
3	73	3	27	12	72	3	28	11
4	76	3	24	11	89	3	11	24
5	89	2	11	22	94	3	6	47
Credit Growth (45/18)								
6	67	6	33	17	67	5	33	16
8	57	5	43	12	56	4	44	9
10	70	5	30	15	72	3	28	10
12	78	4	22	20	89	2	11	16
14	83	4	17	21	94	1	6	23
Credit Growth – GDP Growth (39/18)								
0	82	6	18	34	83	5	17	32
2	85	7	15	47	78	7	22	30
4	74	7	26	26	72	5	28	20
6	74	6	26	22	72	5	28	18
8	79	4	21	21	83	3	17	20
Credit-to-GDP Gap (36/18)								
2	86	3	14	24	78	3	22	12
4	94	3	6	47	89	2	11	22
6	94	2	6	38	89	2	11	18
8	94	2	6	31	89	2	11	18
10	86	2	14	11	78	2	22	8
M2 Growth (40/18)								
8	75	6	25	23	72	7	28	27
10	78	6	23	25	78	5	22	23
12	80	5	20	25	83	3	17	20
14	88	5	13	37	94	3	6	51

(continued)

Table 7. (Continued)

Threshold	All Data				Homogenous Data			
	T 1	T 2	Pred.	NS	T 1	T 2	Pred.	NS
Property Growth (25/18)								
2	88	5	12	42	89	4	11	35
3	88	5	12	44	89	4	11	36
4	92	5	8	65	94	4	6	69
5	96	5	4	124	100	4	0	—
6	92	5	8	61	100	4	0	—
Property Gap (22/18)								
2	68	2	32	6	67	2	33	5
4	68	2	32	6	61	1	39	3
6	73	2	27	8	67	2	33	6
8	82	2	18	11	78	2	22	9
10	82	2	18	10	78	2	22	9
Equity Growth (28/18)								
15	82	9	18	50	83	9	17	53
17	82	9	18	48	83	8	17	51
19	82	9	18	49	83	8	17	51
21	79	8	21	38	78	8	22	35
23	79	7	21	35	78	7	22	30
Equity Gap (26/18)								
0	77	5	23	22	78	5	22	21
5	81	5	19	26	83	5	17	30
10	85	5	15	31	83	5	17	31
15	81	4	19	21	78	5	22	20
20	85	4	15	25	83	4	17	25
Profits (28/18)								
0.40	75	6	25	25	78	8	22	35
0.50	65	7	35	20	74	9	26	34
0.60	69	7	31	24	70	9	30	30
0.70	71	8	29	29	74	8	26	30
0.80	76	8	24	32	78	8	22	35
0.90	83	8	17	46	81	9	19	50
Loss (28/18)								
0.70	68	74	32	229	67	57	33	171
0.60	68	78	32	243	67	67	33	200
0.50	68	81	32	252	63	69	37	187
0.40	73	82	27	301	67	75	33	225
0.30	80	83	20	411	74	75	26	289

(continued)

Table 7. (Continued)

Threshold	All Data				Homogenous Data			
	T 1	T 2	Pred.	NS	T 1	T 2	Pred.	NS
Bank CDS (4/0)								
5	100	0	0	0				
10	50	78	50	156				
15	100	100	0	0				
20	75	86	25	343				
LIBOR-OIS (3/0)								
10	33	75	**67**	113				
30	33	60	**67**	90				
50	33	60	**67**	90				
70	33	71	**67**	107				
75	100	100	0	0				
Credit Spreads (4/0)								
160	50	88	50	176				
180	50	89	50	178				
190	25	84	**75**	112				
200	25	83	**75**	111				
210	25	79	**75**	105				
220	50	87	50	173				

Notes: Threshold: for macroeconomic variables and banking sector conditions in percent; for market indicators in basis points. T1: type 1 error, no signal is issued and a crisis occurs. T2: type 2 error, a signal is issued and no crisis occurs. Pred.: percentage of crises predicted correctly. Bold figures in this column indicate that more than 66 percent of crises are captured. NS: noise-to-signal ratio; fraction of type 2 errors divided by one minus the fraction of type 1 errors. Bold figures in this column indicate the lowest noise-to-signal ratio given that more than 66 percent of crises are captured. For all variables (except profits and market indicators), a signal equal to 1 is issued when the conditioning variable exceeds (is smaller than) the threshold. Otherwise, the signal is equal to 0. A signal of 1 (0) is judged to be correct if a crisis (no crisis) occurs any time within a three-year horizon. The numbers in parentheses next to the name of the variable correspond to the number of crises that are included in the analysis using the sample that includes the available data for that variable (left-hand-side number) and the homogenous sample (right-hand-side number), respectively.

Table 8. The Performance of Different Credit-to-GDP Gaps

Threshold	All Data (36)				Homogenous Data (18)			
	T 1	T 2	Pred.	NS	T 1	T 2	Pred.	NS
Real Time, HP $\lambda = 400{,}000$ (Standard)								
2	11	38	**89**	43	6	45	**94**	48
4	17	29	**83**	35	11	36	**89**	41
6	25	21	**75**	28	17	27	**83**	33
8	31	16	**69**	23	22	20	**78**	26
10	33	11	**67**	**16**	22	14	**78**	18
12	47	8	53	14	33	10	**67**	**15**
Two-Sided Filter (Past and Future Known), HP $\lambda = 400{,}000$								
2	17	27	**83**	32	11	24	**89**	27
4	25	18	**75**	24	17	17	**83**	20
6	28	12	**72**	**17**	22	11	**78**	14
8	39	8	61	14	33	7	**67**	**10**
10	50	6	50	11	44	4	56	8
12	61	4	39	9	56	3	44	7
Real Time, HP $\lambda = 1{,}600$								
1	14	41	**86**	47	17	46	**83**	55
1.5	19	33	**81**	41	28	37	**72**	52
2	22	26	**78**	34	33	31	**67**	**46**
2.5	31	21	**69**	**30**	39	24	61	40
3	39	16	61	26	39	19	61	31
3.5	39	12	61	20	39	14	61	23
4	47	9	53	18	50	11	50	22
Real Time, Linear Trend								
4	17	29	**83**	35	6	37	**94**	40
6	22	22	**78**	28	11	29	**89**	32
8	33	15	**67**	**22**	22	21	**78**	28
9	36	12	64	19	22	19	**78**	24
10	44	10	56	18	33	15	**67**	**23**
12	58	7	42	16	44	11	56	19

Notes: Threshold: in percent. T1: type 1 error, no signal is issued and a crisis occurs. T2: type 2 error, a signal is issued and no crisis occurs. Pred.: percentage of crises predicted correctly. Bold figures in this column indicate that more than 66 percent of crises are captured. NS: noise-to-signal ratio; fraction of type 2 errors divided by one minus the fraction of type 1 errors. Bold figures in this column indicate the lowest noise-to-signal ratio given that more than 66 percent of crises are captured. For all variables, a signal equal to 1 is issued when the conditioning variable exceeds the threshold. Otherwise, the signal is equal to 0. A signal of 1 (0) is judged to be correct if a crisis (no crisis) occurs any time within a three-year horizon. The numbers in parentheses next to "All Data" and "Homogenous Data" correspond to the number of crises that are included in the analysis using the respective sample. Real-time trends use information available up to each point in time in which the signal is issued. The two-sided filter uses all available information in the data set.

Table 9. The Performance of Different Signaling Horizons

Threshold	All Data (36)				Homogenous Data (18)			
	T 1	**T 2**	**Pred.**	**NS**	**T 1**	**T 2**	**Pred.**	**NS**
Year 1 & 2 & 3 (Standard)								
4	17	29	**83**	35	11	36	**89**	41
5	19	25	**81**	31	17	31	**83**	37
6	25	21	**75**	28	17	27	**83**	33
7	31	18	**69**	26	22	23	**78**	30
8	31	16	**69**	23	22	20	**78**	26
9	31	13	**69**	19	22	17	**78**	21
10	33	11	**67**	**16**	22	14	**78**	18
11	39	9	61	15	28	12	**72**	17
12	47	8	53	14	33	10	**67**	**15**
Year 1								
4	25	32	**75**	43	17	41	**83**	50
5	31	28	**69**	40	22	36	**78**	47
6	33	24	**67**	**36**	28	32	**72**	45
7	39	21	61	34	33	28	**67**	43
8	39	18	61	30	33	25	**67**	38
9	39	15	61	25	33	21	**67**	32
10	39	13	61	21	33	18	**67**	28
11	42	11	58	19	33	16	**67**	**24**
12	50	9	50	19	39	14	61	23
Year 2								
4	22	31	**78**	39	17	39	**83**	47
5	28	26	**72**	36	22	34	**78**	43
6	33	23	**67**	**34**	22	30	**78**	38
7	36	19	64	31	22	26	**78**	33
8	39	17	61	28	28	23	**72**	31
9	44	14	56	25	33	19	**67**	**28**
10	50	12	50	24	39	16	61	27
11	58	10	42	24	50	14	50	28
12	61	8	39	22	50	12	50	24
Year 3								
4	28	29	**72**	40	17	36	**83**	44
5	31	25	**69**	**36**	22	31	**78**	**40**
6	42	21	58	37	33	27	**67**	41
7	44	18	56	33	39	23	61	38
8	44	16	56	28	39	20	61	33
9	47	13	53	24	44	17	56	30
10	53	11	47	23	44	14	56	25
11	61	9	39	23	50	12	50	24
12	64	8	36	21	50	10	50	20

(continued)

Table 9. (Continued)

Threshold	All Data (36)				Homogenous Data (18)			
	T 1	**T 2**	**Pred.**	**NS**	**T 1**	**T 2**	**Pred.**	**NS**
Year 1 & 2								
4	19	31	**81**	38	11	39	**89**	44
5	28	26	**72**	36	22	34	**78**	43
6	28	23	**72**	31	22	30	**78**	38
7	33	19	**67**	29	22	26	**78**	33
8	33	17	**67**	**25**	22	23	**78**	29
9	36	14	64	22	28	19	**72**	26
10	39	12	61	19	33	16	**67**	24
11	42	10	58	17	33	14	**67**	**21**
12	50	8	50	17	39	12	61	19
Year 2 & 3								
4	17	29	**83**	35	11	36	**89**	41
5	19	25	**81**	31	17	31	**83**	37
6	31	21	**69**	31	17	27	**83**	33
7	33	18	**67**	**27**	22	23	**78**	30
8	36	16	64	24	28	20	**72**	28
9	36	13	64	20	28	17	**72**	23
10	42	11	58	19	28	14	**72**	**19**
11	56	9	44	20	44	12	56	22
12	58	8	42	18	44	10	56	18

Notes: Threshold: in percent. T1: type 1 error, no signal is issued and a crisis occurs. T2: type 2 error, a signal is issued and no crisis occurs. Pred.: percentage of crises predicted correctly. Bold figures in this column indicate that more than 66 percent of crises are captured. NS: noise-to-signal ratio; fraction of type 2 errors divided by one minus the fraction of type 1 errors. Bold figures in this column indicate the lowest noise-to-signal ratio given that more than 66 percent of crises are captured. A signal equal to 1 is issued when the credit-to-GDP gap exceeds the threshold. Otherwise, the signal is equal to 0. A signal of 1 at time t is judged to be correct (false) if a crisis (no crisis) occurs over the following signaling horizons: (i) "year 1 to 3": quarters $t+1$ to $t+12$, (ii) "year 1": quarters $t+1$ to $t+4$, (iii) "year 2": quarters $t+5$ to $t+8$, (iv) "year 3": quarters $t+9$ to $t+12$, (v) "year 1 and 2": quarters $t+1$ to $t+8$, and (vi) "year 2 and 3": quarters $t+5$ to $t+12$. The numbers in parentheses next to "All Data" and "Homogenous Data" correspond to the number of crises that are included in the analysis using the respective sample.

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