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Countercyclical capital buffers: exploring options

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Abstract

This paper provides some general lessons for the design of countercyclical capital buffers. Its main empirical contribution is to analyse conditioning variables which could guide the build-up and release of capital. A major distinction for countercyclical capital schemes is whether conditioning variables are bank-specific or system-wide. The evidence presented in the paper indicates that the idiosyncratic component can be sizeable when a bank-specific approach is used. This makes a system-wide approach preferable, for which the best variables as signal for the pace and size of the accumulation of the buffers are not necessarily the best for the timing and intensity of the release. The credit-to-GDP ratio seems best for the build-up phase. Some measure of aggregate losses, possibly combined with indicators of credit conditions, seem to perform well for signalling the beginning of the release phase. Nonetheless, the analysis indicates that designing a fully rule-based mechanism may not be possible at this stage as some degree of judgment seems inevitable. A parallel exercise indicates that reducing the sensitivity of the minimum capital requirement is an important element of a credible countercyclical buffer scheme.

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I. Introduction[6]

The financial crisis has accelerated efforts to provide policy makers with frameworks and tools to address the procyclicality of the financial system. This paper assesses various options for one particular tool, namely countercyclical capital buffers. It draws on cross-country empirical evidence and provides some general lessons for the design of countercyclical prudential capital standards.

The proximate objective of countercyclical capital standards is to encourage banks to build up buffers in good times that can be drawn down in bad ones.[7] Buffers should not be understood as the prudential minimum capital requirement. Instead, they are unencumbered capital in excess of that minimum, so that capital is available to absorb losses in bad times. Countercyclical capital buffer schemes can be thought of as having two closely related ultimate objectives (BIS (2010)). One is to limit the risk of large-scale strains in the banking system by strengthening its resilience against shocks. The second is to limit the banking system amplifying economic fluctuations. In most circumstances, the difference between the objectives is not significant. For example, it is precisely when the financial system experiences large losses that its impact on the macroeconomy is strongest, through the induced credit contraction and asset fire sales. However, the relative weight assigned to the two objectives can colour the assessment of various schemes. For instance, a policy maker with a focus on the first objective may be less tolerant of reductions in capital buffers in bad times even if this helps to sustain overall lending.

An underlying rationale for the scheme is that risks tend to build up in good times, but their consequences materialise only with a considerable lag.[8] This build-up reflects limitations in current risk measurement practices as well as distortions in the incentives of individual financial institutions (FSB (2009)). The accumulation of buffers in good times is a way of addressing this problem. It strengthens the defences of each individual institution, and therefore of the system as a whole. And to the extent that it acts as a kind of dragging anchor, leaning against the build-up of credit expansion and risk-taking, it can also reduce the likelihood that strains emerge after the good times have ended.

Any effective scheme would need to have a number of desirable features. First, it would identify the *correct timing* for the accumulation and release of the capital buffer. This means correctly identifying good and bad times. Second, it would ensure that the *size* of the buffer built up in good times is sufficiently large to absorb losses without triggering serious strains. Third, it would be *robust to regulatory arbitrage*, including manipulation. Fourth, it would be enforceable internationally. Fifth, it would be as *rule-based* as possible, acting as an automatic stabiliser. In particular, this would ease the pressure on prudential authorities to refrain from taking restrictive measures in good times. Sixth, it should have *a low cost of implementation.* Finally, it would be *simple and transparent*.

In addition, it is important that any such scheme builds on current prudential instruments. In what follows, this is taken to imply two constraints. First, the minimum capital requirement should be treated as floor for capital at all times. This rules out adjustment factors that call for reductions in capital below that minimum. Such adjustments could undermine the credibility

[6] We are very grateful to the Norges Bank for providing the data used in this analysis. We would also like to thank Kostas Tsatsaronis and Jesus Saurina for providing substantial and valuable inputs, Stephen Cecchetti for helpful comments and Jakub Demski and Angelika Donaubauer for excellent research assistance. The views expressed are those of the authors and not necessarily those of the respective institutions.

[7] Note that buffers can also be build up and run down using dynamic provisions (ie the general loan loss provisions applied in Spain since mid-2000). Here we only focus on capital buffers.

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

of current rules and would be more likely to be disregarded by the market. However, as we establish in Section IV, current minimum capital requirements may show a significant degree of procyclicality, which has to be considered when designing the scheme. Second, the scheme should retain as far as possible the cross-sectional differentiation of credit risk. This is still compatible with smoothing the time variation and cyclical sensitivity of the minimum requirement, but it means that the adjustment factor should be multiplicative, acting as a scalar for the minimum.

The main empirical contribution of this paper is to analyse conditioning variables which could guide the build-up and release of capital. A major distinction for countercyclical capital schemes is whether conditioning variables are bank-specific (bottom-up) or system-wide (top-down). The evidence presented in the paper indicates that the idiosyncratic component can be sizeable when a bottom-up approach is employed. This would imply large differences in the values of the adjustment factors across banks, even in times when broad financial stability pressures build up. In addition, the persistence of bank-specific factors can be very low, so that the volatility in the target for the countercyclical capital buffer could be substantial, sometimes changing size and direction considerably in several successive periods.

For a top-down approach, the analysis shows that the best variables, which could be used as signals for the pace and size of the accumulation of the buffers, are not necessarily the best signalling the timing and intensity of the release. Credit seems to be preferable for the build-up phase. In particular when measured by the deviation of the credit-to-GDP ratio from its trend, it has proven leading indicator properties for financial distress. The corresponding data are also available in all jurisdictions, in contrast to other variables such as CDS spreads. An additional benefit of using the credit-to-GDP ratio as conditioning variable would be that a time-varying target on credit expansion in good times could also restrain the credit boom. Some measure of aggregate banking sector losses, possibly combined with indicators of credit conditions, seems best for signalling the beginning of the release phase. Whether and how to guide the pace and intensity of the release is less clear. In general, a prompt and sizeable release of the buffer is desirable as a gradual release could reduce the buffer's effectiveness.

Overall, our empirical analysis indicates that a fully rule-based mechanism may not be practicable at this stage. Some degree of judgment, both for the build-up as well as the release phase, seems inevitable.

The paper is organised as follows. Section II provides a taxonomy of possible schemes. Section III compares a number of options based on data drawn from a sample of countries. Section IV considers the impact of the cyclical sensitivity in minimum capital requirements. Section V summarises the lessons from the analysis. Various annexes provide further background information.

II. A taxonomy of possible schemes

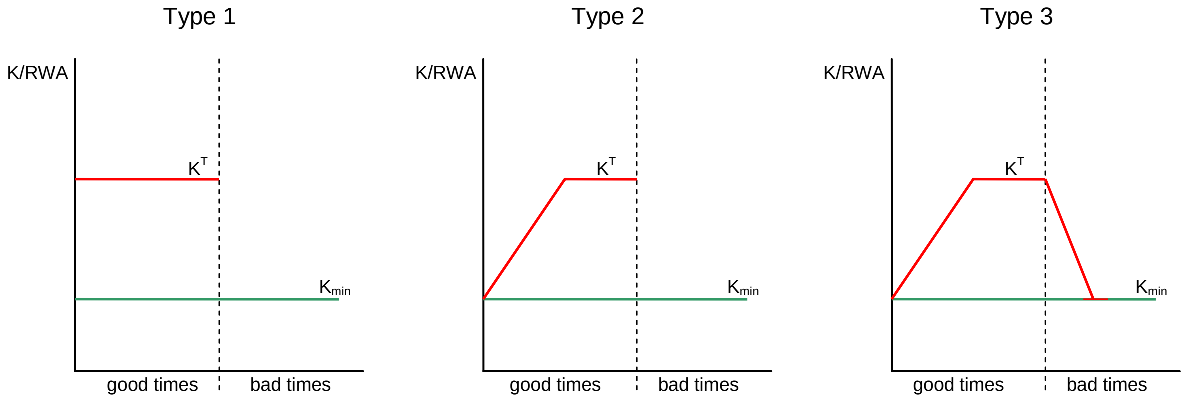
Any scheme will need to involve two elements: (i) choosing a conditioning variable that signals the time to build up and release capital buffers; and (ii) choosing an adjustment factor that determines how changes in the conditioning variable map into capital requirements. The overall scheme will also depend on the cyclicality of the minimum capital requirement with respect to which the buffer is calculated. The main focus of this paper is on the first of these issues.

Two types of rules for the creation of buffers are in principle possible.

The first type involves having the *minimum capital requirement itself moving countercyclically*, rising in the expansion phase and falling in the release phase. In this case, a buffer is created to the extent that during the release phase the requirement falls, freeing capital. The buffer is effective to the extent that the minimum falls faster than the speed at which losses are incurred. This type of rule has attracted considerable attention (eg Gordy (2009)). However, it would imply that the capital minimum would have to fall in bad times and hence would call for adjustment factors that set regulatory capital below the current minimum requirements. As such, it violates one of the constraints noted in the introduction and will not be considered.

Graph II.1

Types of countercyclical capital buffer schemes



Note: K/RWA = ratio of capital to risk-weighted assets; K_{min} = minimum capital requirement; K^T = target (capital).

The second type of rule involves *setting a target above the minimum*, with the gap between the two moving countercyclically, rising in good times and falling in bad times (Graph II.1). One extreme form would be to have a fixed buffer, X, during good times (so that capital would equal the minimum + X%) and no required buffer in bad times when the regulatory minimum would become the relevant constraint (Graph II.1, left-hand panel). Fixed capital targets can be automatically stabilising to the extent that their incidence, or “bite”, varies over the cycle. At the same time, fixed instruments need to be designed with care to avoid inducing procyclicality. For example, if binding during the upswing, minimum capital requirements can constrain risk-taking. But if they become binding as strains emerge, they can encourage hasty shedding of risky assets and tighter credit conditions (see BIS (2010)).

Another possibility would be to have an increasing target in good times, possibly until it reaches some upper limit. As we explore below, the build-up could be related to some *conditioning variable* (eg credit, earnings, a credit spread). Release could either be instantaneous once bad times arrive (see Graph II.1, middle panel) or gradual, if it is linked to the same or another conditioning variable (see Graph II.1, right-hand panel). Various combinations are possible. What follows is an exploration of the options within this second broad class of measures.

Capital targets can also take two forms. They can be *hard targets*, to be met at all times. In effect, these act as required minima. While additional capital targets are in place, therefore, they cannot act as buffers. As with any minima, a buffer would be created only to the extent that the target falls, and it would be effective only if losses accumulated at a slower pace. Alternatively, they can be *soft targets*, in which case banks are encouraged to move towards the target through a possibly graduated supervisory penalty function. In this case, depending on the nature of the penalties, amounts of capital below the target can still be used to some extent to absorb losses.[9]

Schemes may also vary in terms of the choice of conditioning variable, which determines how fast the buffer is accumulated and released. A major distinction here is between conditioning variables that are bank-specific (bottom-up) or system-wide (top-down). In the case of bank-specific conditioning variables, the schemes can be implemented by considering banks on a stand-alone basis; this is not possible otherwise.

Each option has its pros and cons. Bottom-up approaches accommodate idiosyncratic factors more easily and may be simpler to implement. By contrast, top-down ones specifically address the system-wide dimension that lies at the heart of procyclicality. From this perspective, the accommodation of idiosyncratic factors is not necessarily a desirable feature. For example, if a bank incurs losses in good times when others are performing well, and hence for idiosyncratic reasons, its problems would not result in a material aggregate contraction in credit and distress selling. As a result, it is not clear why it should be allowed to use a buffer set specifically to address generalised losses and procyclicality.[10]

This issue interacts with the choice between hard and soft targets. A soft target can more easily accommodate idiosyncratic losses in good times, but this may not be desirable in the current context. In effect, the bank would be in a similar situation to the current one, when a breach of the regulatory minimum is heavily penalised. As a result, it would have to hold a buffer above the target to absorb idiosyncratic shocks. From this perspective, the choice between hard and soft targets would have more to do with questions concerning the desired degree of regulatory control over how quickly the buffer is accumulated and released.

In assessing the performance of the various schemes, the distinction between risk-weighted and unweighted assets is critical. The *incentive* for banks to retrench in bad times is linked to the amount of capital in excess of the regulatory constraint, which is set in risk-weighted asset terms. However, the *impact* of that retrenchment on the economy is related to the amount of capital in relation to risk-unweighted assets or loans, which determines how far banks need to shrink their balance sheet to economise on capital. In bad times, therefore, the rise in risk-weighted assets associated with higher measured risk generates a double blow: it erodes the capital cushion; and, by raising the ratio of risk weighted assets to unweighted assets, it calls for a larger retrenchment per unit of risk-weighted assets (Graph II.2). Moreover, decisions to cut risk-weighted assets by altering the *composition* of the balance sheet towards safer investments will also be procyclical. An obvious example is a reduction in credit to the private sector in order to finance the purchase of government securities.

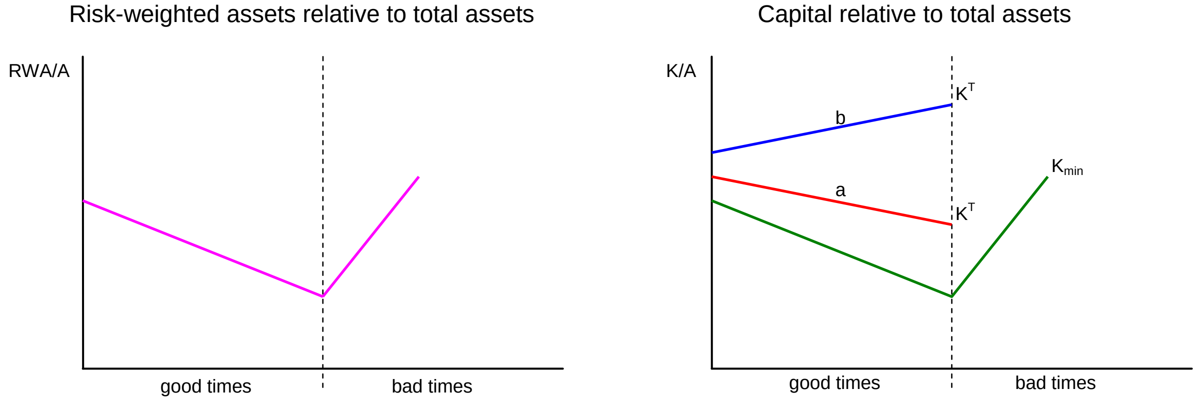
As good times continue, on the other hand, banks' risk-weighted assets relative to total assets tend to fall. Depending on the calibration of the countercyclical capital scheme, this could imply that the overall level of the capital target relative to total assets falls in the run-up to bad times, even if the perfect conditioning could be found (path a or b in Graph II.2, right-hand panel).

[9] In practice, the distinction between the two is not black and white, as it all depends on the penalties incurred when the hard target is breached. A hard target would mean that the penalties are such that institutions would normally avoid a breach, so that the supervisors can expect them to remain above it. For current purposes, however, it is useful to make a sharper distinction, in order to better highlight the trade-offs involved.

[10] This would be so unless the bank in question was large enough relative to the overall banking system. In that case, however, the problems would indeed be systemic and the distinction between idiosyncratic and system-wide factors would disappear.

Graph II.2

Risk-weighted versus unweighted assets



Note: A = unweighted assets; RWA = risk weighted assets; K_{min} = minimum capital requirement; K^T = capital target; .a and b refer to two possible paths for the target, depending on the combination of the conditioning variable and the adjustment factor;

This means that *the procyclical impact of a scheme cannot be assessed purely on the basis of its effect on the relationship between the buffer and risk-weighted assets*. It is also necessary to consider the relationship between the buffer and unweighted assets, which we will analyse in Section IV. In general, the greater the variability in the ratio of risk-weighted to unweighted assets, the stronger the procyclical effect. This is important for the correct calibration of the schemes.

III. Assessing possible schemes

Next, we consider (i) the choice of triggers for the transition from the accumulation to the release phases and (ii) the rules for the accumulation and release. We first examine top-down rules, based on system-wide variables, and then bottom-up ones, based on their bank-specific counterparts. In addition, we evaluate the behaviour of targets in relation to the prudential minimum, postponing to the following section the discussion of the impact of the cyclical sensitivity of the minimum. Therefore, the analysis is couched exclusively in terms of risk-weighted assets.

Identifying good and bad times

In stylised terms, an ideal conditioning variable would be a coincident indicator of the financial cycle. It would induce a build-up of the buffer to a sufficient level in good times, and release it with the right speed and in the right amount in bad times. Good and bad times would coincide with the expansionary and contractionary phases of the cycle.

In practice, matters are not so simple. For a start, it is not clear how the financial cycle should be measured. A number of variables come to mind, such as measures of bank performance (eg earnings, losses or asset quality, such as non-performing loans), financial activity (eg credit), as well as the cost and availability of credit (eg credit spreads). Moreover, the financial and real (output) cycles do not necessarily coincide and their relationship can vary over time. In particular, severe financial strains do not arise in every recession. And, as will be seen below, the leads and lags between the peaks and troughs of various financial indicators and output are both significant and variable.

To narrow down the question, it is probably best to revisit the objectives of the exercise (FSB, 2009): Banks should build up buffers so that they can absorb losses in bad times. And banks should not be a source of credit contraction induced by financial strains on their balance sheets. Rather, they should act as far as possible more as shock absorbers than amplifiers.[11]

This suggests that the transition from good to bad times can be identified by a mix of two factors: some measure of aggregate *gross* losses at banks, probably best normalised by the size of balance sheets, and an indicator of whether the banking sector is a source of credit contractions or not (Table III.1). The transition from bad to good times could be identified in the same 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.

Table III.1

Criteria to identify bad times

		Banking sector source of credit contraction	
		Yes	**No**
Bank losses	**High**	Bad times	Bad times[1]
	Low	Bad times?[2]	Good times

[1] Even if banks experience sizeable losses, credit supply may not be constrained because banks may wish to protect customer relationships. Buffers should still be released to help forestall a credit crunch. [2] It would be appropriate to release the buffer if credit supply constrains reflect a *prospective* erosion of the capital cushion, owing to expected losses not yet recorded in the accounts (eg as a result of backward-looking accounting practices).

To illustrate how bad times could be identified in practice, we draw on data for the United States, the country for which most data are available. An ideal measure of aggregate gross losses would capture all sources of losses independent of whether those arise from credit, market or other risks. Furthermore, losses in some institutions would not be offset by gains at others, since the response is bound to be highly asymmetric, given the nature of the constraints.[12] Such a measure does, however, not exist, in particular for a sufficiently long time series. As proxy for gross aggregate losses in the example we, therefore, use bank charge-offs. While this variable covers only credit risk losses, this disadvantage is mitigate by its close relationship with the down leg of the credit cycle.

Credit supply constrains are harder to measure. Credit conditions for the banks are indicative of constraints on the supply of funds to them, which in turn could cause retrenchment. Credit conditions for the banks' customers, on the other hand, can capture signs of a credit crunch for the economy more generally, although they need not result from weakness in the banks' own balance sheet. They might simply signal a deterioration in the credit quality of

[11] Moreover, the build-up of regulatory buffers could also help to reduce the likelihood of financial distress by restraining risk-taking during the expansionary phase of the financial cycle.

[12] See (eg) Borio and Zhu (2008) for a review of the literature on this topic.

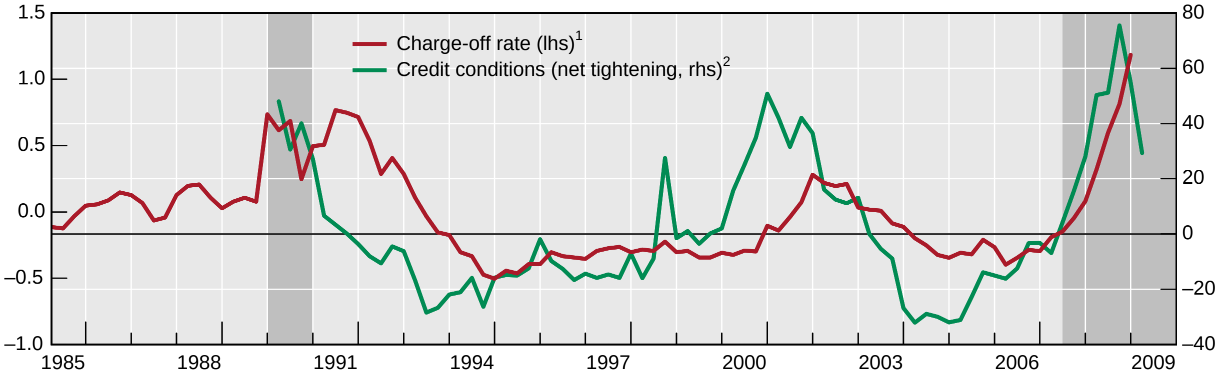
borrowers. If so, they may not be particularly relevant, as the retrenchment by the banks would reflect changing demand, rather than credit supply restrictions.

As proxy for credit conditions we use the net tightening series from the Senior Loan Officer Survey. This variable reflects the tightening of credit conditions for bank customers only. Thus it does not specifically reflect funding conditions for the banks themselves, although it may do so indirectly. Furthermore, the Senior Loan Officer Survey reports net-tightening, ie the change in credit standards, rather than the level. By construction it can therefore be the case that this variable indicates an easing of conditions, even though credit supply is severely constrained but banks cannot or do not want to tighten further (ie net-tightening is zero). That said, empirically this variable is very appealing as it has been found to be very helpful in anticipating a credit crunch and its effect on the business cycle (Lown et al (2000) and Lown and Morgan (2006)). But it is unclear whether this would hold in the future if the net-tightening series would be used to guide the release of capital buffers, as credit conditions are based on survey data which could be easily manipulated.

The shaded area in Graph III.1 reflects periods that have previously been identified as episodes of banking distress in the literature: the early 1990s and the current episode. Since the criteria may not be identical, the precise timing for the beginning of the stress in the two cases is highly approximate (Q1 1990 and Q3 2007). For the two proxy variables, we filter out the cyclical component by taking deviations from a 15-year rolling average.

Graph III.1

Charge-offs and credit conditions for the United States



The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

[1] Loans and leases removed from the books and charged against loss reserves, as a percentage of average total loans. [2] Difference between the number of banks that reported a tightening on conditions applied to C&I loans to large and medium-sized firms in the Senior Loan Officer Opinion Survey and those that reported an easing. Positive (negative) values indicate a lesser (greater) willingness of banks to grant loans.

Sources: Senior Loan Officer Opinion Survey on Bank Lending Practices; national data.

The graph suggests a number of observations. First, both periods of banking distress are characterised by high charge–off rates and a tightening of credit conditions. Second, a tightening of credit terms appears to precede the increase in charge-off rates, although the lead is quite variable (and the data is incomplete for the episode in the late 1980s to early 1990s). This may reflect the rather backward-looking nature of charge-offs. Third, on the basis of the indicator of credit conditions alone, the episode in the downturn of 2001 looks comparable to the other two. However, charge-offs did not increase as much and, in fact, banks experienced far less strains. In this case, it would seem that the deterioration in the credit quality of borrowers did not greatly affect the sector's financial strength. As a result, the tightening of lending terms was more of a reflection of borrowers' conditions than of any funding constraints on the part of the banks. Overall, this would indicate that times were not bad for banks.

What should be the relative weight of aggregate losses and credit conditions more generally? Arguably, aggregate losses are critical. Whenever generalised large losses are incurred, buffers should be released, even if no signs of a credit tightening have yet emerged. This is what buffers are for and their use would help forestall a credit crunch. But the choice can sometimes be less obvious. It is possible to imagine circumstances in which *prospective* losses, not yet recorded in the accounts, could induce banks to retrench (ie bank losses are low and the banking sector is a source of credit contraction in Table III.1). This could occur, for example, if forward-looking provisioning is highly restricted. For example, one could argue that buffers should have been released in the third quarter of 2007 in many countries, as serious strains emerged in the interbank markets, even if, except for mark-to-market losses, overall losses did not appear to be that large at the time. Accounting conventions can have a first-order effect on the dynamics of financial strains and on the interaction between losses, asset quality and liquidity constraints.

This discussion points to two preliminary conclusions. First, (gross) aggregate losses, measured relative to some neutral historical level (eg a long-term average), seem to be a good variable to identify the need to release capital and, by implication, the target buffer that has to be accumulated before their emergence. A measure of credit conditions can also provide complementary information to address cases in which losses may fail to perform their signalling role effectively. Second, the preliminary analysis suggests that identifying the precise timing of the release of the buffer may require some judgement.

In what follows, we assess the performance of various indicators for the accumulation and release of the buffers in relation to the above benchmark for bad times. Bad times are identified primarily by reference to measures of aggregate losses and episodes of serious banking distress or crises recognised as such in previous empirical work (Laeven and Valencia (2008) and Borio and Drehmann (2009)). In the following graphs, initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy are highlighted by shaded areas. In addition, we show, if available, measures of gross losses. But we can only approximate them with narrower indicators such as charge-offs (United States) or specific loan loss provisions (Norway and Spain).

Accumulating and releasing capital buffers

Are there system-wide or aggregate variables that can effectively act as conditioning variables, so as to guide the pace of the accumulation and release of the buffers? While in principle the same variable could perform the two functions, in practice this need not be the case.

One possible problem could be that the variables are unable to capture the "temperature" of good times. The ideal variable for signalling the speed and extent of the accumulation of the buffer would be a proxy for the build-up of risks in good times. This would therefore be the best *leading indicator* of future banking distress.

This property provides some clues about the likely performance of possible candidates. To capture the "temperature" well, the relevant variable should at a minimum exhibit considerable variation during the build-up phase, away from its long-term average, and the more so, the greater the pressure on financial stability. This largely rules out variables that can, in fact, act as very good proxies for the release phase, such as non-performing loans or loan losses, as they can never fall below zero in good times.[13] It may also militate against revenues or earnings, which might not be sufficiently sensitive to the cycle; for instance, competitive pressures may compress margins during the expansion. By contrast, variables such as credit and asset prices, especially the prices of residential property, may be useful. In particular, credit booms are probably the best single-variable leading indicator of banking distress; and *combinations* of credit and asset price deviations from long-term trends are even better (eg Borio and Lowe (2002) and Borio and Drehmann (2009)).[14] Credit spreads may also contain helpful information: high risk-taking, reflecting both low perceptions of risk and high risk appetite, is a natural precursor of financial strains. In this case, however, the lower boundary on the compression of risk spreads may limit their information content and complicate calibration.

A second, more fundamental, problem is that it is hard to imagine how the same variable could act as the best leading *and* contemporaneous indicator of financial strains.[15] And this is precisely what would be required for it to be the best signal for the accumulation *and* release phases. For example, credit expansion can exhibit considerable inertia, losing momentum with a lag following the materialisation of distress. This may reflect, for instance, the effect of customers' drawing down their lines of credit and the banks' incentives to protect customer relationships. In the case of the credit-to-GDP ratio, it may also stem from the weakening in economic activity. Similarly, asset prices may start falling too early relative to the emergence of strains.

We next examine empirically the performance of a number of possible conditioning variables. The variables assessed are divided into three groups. The first includes aggregate macroeconomic variables, the second measures of banking sector performance and the final one proxies for the cost of funding.

Aggregate macroeconomic conditions

Measures of aggregate output and (broadly defined) credit are the most natural indicators for the state of the financial cycle. Asset prices may also be useful aggregate indicators as they tend to rise strongly ahead of systemic banking crises. Aggregate macro indicators in general offer the advantage that they are immune to strategic manipulation by individual institutions, even though they are still influenced by the collective behaviour of the banking sector. In addition, most macroeconomic series are widely available and therefore such indicator variables could be used in many countries.

Real GDP growth: this is the most natural indicator of the aggregate business cycle for an economy. However, the business and the financial cycle, although intertwined, need not be fully synchronised at all points in time. In particular, financial strains do not arise with every recession.

Aggregate real credit growth: the cycle is often defined with reference to credit availability. Aggregate credit growth could be a natural measure of supply, in particular if not only bank credit but all other sources of credit are taken into account. As boom periods are

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[13] In other words, their variation in good times is bound to be quite small, largely reflecting idiosyncratic factors, and hence limiting their usefulness in differentiating how far pressures on financial stability build up.

[14] For a survey of the empirical evidence on leading indicators of banking distress, see Demirgüç-Kunt and Detragiache (2005).

[15] Conceptually, a perfect leading indicator could also provide perfect signals that a crisis will emerge with certainty at a particular point in time in the future. However, if this would be the case, banks would try to avoid the crisis by restructuring their balance sheets now. This would result either in an immediate crisis or no crisis at all. Hence, such an indicator cannot be envisaged.

characterised by rapid credit expansion and declines in overall credit are typically considered symptomatic of a credit crunch, deviations of credit growth from a trend could be an informative variable to use. Due to data limitations, we use bank credit in our analysis except for the US, where a broad credit measure is used.

Credit-to-GDP ratio: The credit-to-GDP ratio provides a normalisation of the credit variable to take into account the fact that credit demand and supply grow in line with the size of the economy. In addition, there is a strong link, historically, between faster than average credit-to-GDP growth and banking crises. In the analysis we consider deviations of the credit-to-GDP ratio from its long-term trend, to take account of possible changes in the long-run level of the ratio, for example due to financial deepening (for details see Annex 1).[16] Therefore, we also refer to it as the credit-to-GDP gap.

Even though the credit-to-GDP gap normalises the volume of credit by GDP and corrects for changes in the long run trend, it is essentially a statistical measure. Therefore, it may not take fully into account the equilibrium level of lending given the state of the economy. In Annex 2 we compare the performance of the credit-to-GDP gap as well as credit growth with a model-based measure that takes account of the deviation of bank lending from its long-term equilibrium value. The latter is obtained from loan demand and supply equations that are dependent on a set of macroeconomic factors. These include interest rates, which are the main channel through which banks set their lending standards. The analysis is undertaken in a reduced form for the US. It shows that a credit-to-GDP gap issues the strongest signals ahead of the current crisis. The model-based measure performs worse, because the period prior to the crisis was characterised by very low interest rates. Even if the growth of lending was quite high, loan demand was expected by the model to be even greater. This indicates that in periods of low interest rates the model-based measure would have to be corrected even further to take account of a potential risk-taking channel (Borio and Zhu, 2008). Given that countercyclical capital schemes should be simple and transparent, this makes the model-based measures less attractive.

Asset price growth: Financial assets and in particular property prices tend to show exceptionally strong growth in periods that precede systemic banking events. They fall precipitously during periods of financial stress. Similar to the credit-to-GDP ratio, we consider deviation of aggregate property prices from their long-term trend, where aggregate property prices are a value-weighted average of residential and commercial property prices.[17]

Banking sector activity

Aggregate measures of bank activity tend to be coincident with the broader business and financial cycle. Linking the countercyclical instrument to the growth rate of lending or bank income can be motivated on the basis of attempting to smooth the intermediation (credit) cycle measured more narrowly as in relation to banks as opposed to the financial sector at large. The cycle in this case could be identified with fluctuations in measures of bank performance and profitability such as net revenue measures or the expenses banks face, especially if these relate to credit costs. Periods of high bank profitability are typically periods when banks tend to also increase their intermediation activity through rapid credit growth and risk-taking. Benign economic conditions are also associated with low realised credit costs on

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[16] As explained in detail in Annex 1, the credit-to GDP gap is calculated as the difference between the credit-to GDP ratio and a trend derived by a one-sided HP filter using a smoothing parameter of 400,000.

[17] For brevity, equity prices are not included as their performance is not as good as property prices (see Borio and Drehmann (2009)). The property price gap is defined as the deviation of the property price index minus its trend, normalised by the trend. As for the credit-to-GDP gap, the trend is calculated by a one-sided HP filter using a smoothing parameter of 400,000.

banks' portfolios. These are therefore periods when internal capital resources (for instance through retained earnings) are more easily available and when buffers can be accumulated for use in more strenuous periods.

Bank credit growth (also normalised by GDP): see description above.

Banking sector profits: This is a key indicator of performance for the sector. Earnings are high in good times and quickly reflect losses in times of stress. However, profit figures can be the subject of strategic management by banks that can distort their information content. A possible mitigator of this concern would be that profits are linked to incentives within the banks since they determine performance-related pay and are also under the scrutiny of analysts and shareholders. In the analysis below we focus on pre-tax profits relative to total assets, but different profitability measures are compared in Annex 3.

Aggregate losses: This indicator of performance focuses on the cost side (non-performing loans, provisions etc). The financial cycle is frequently identified by the rise and fall of the realised losses. Countercyclical capital instruments based on losses can be calibrated so that they increase the build-up of cushions or buffers in periods when the incidence of losses are low and release them when they increases. Given data limitations, we focus on credit related losses and use, depending on the country, non-performing loans, write-offs or charge-offs relative to total assets.

Cost of funding

This category focuses on the cost to banks of raising funds. The basic idea is that by identifying the cycle with fluctuations in the cost of funding, the rule would create incentives for banks to raise funds in times when these are relatively cheap and allow them to use these reserves in periods of stress when such funding becomes more expensive.

Banking sector credit spreads (indices): These are indicators of vulnerabilities in the banking sector (in the sense of the market assessment of the risk of bank failures). By being closely tied to the financial condition of banks they may be subject to manipulation by them, a drawback mitigated by relying on broad indices where they exist. In the analysis we will look at the average of CDS spreads for the largest banks in each country.

Cost of liquidity: These are indicators of the average cost that the banking sector has to pay to raise short-term liquidity. They are closely linked to banks' health and the aggregate funding conditions in markets. While during normal times interbank markets distribute liquidity seemingly without friction, severe strains emerge rapidly during crises. Such 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 particular during a crisis because of increased uncertainty, dispersion in credit quality across banks and greater incentives to strategically misreport funding costs (Gyntelberg and Wooldrige, 2008). By construction, interbank rates such as Libor are not a transaction-based price measure but an index based on a daily survey amongst a number of panel banks, which would open the door for strategic manipulation.[18] In the analysis we consider Libor-OIS spreads.

Corporate bond spreads (aggregate average): An indicator of credit quality for the economy at large and a point-in-time measure of (credit) risk. Periods of boom are typically characterised by spreads that are lower than their average levels, while periods of stress are

[18] For example, for the construction of the Libor survey banks are asked "*At what rate could you borrow funds, were you to do so by asking for and then accepting inter-bank offers in a reasonable market size just prior to 11 am?".* Quotes are then averaged and the highest and lowest quartiles are dropped.

often marked by rapidly widening spreads. Spreads can also be viewed as indicators of the average cost of borrowing in the economy, including by banks, and thus be used in a tool that targets the smoothing of funding costs.

Overall, the empirical analysis is hampered by limitations in data availability. Most data are available for macro conditions. There is only limited information on aggregate indicators for banking conditions, while data availability for funding costs is even more limited. In practice, the frequency of data releases is also crucial. Whereas market based conditioning variables are available daily, macroeconomic times series are generally released quarterly and indicators of banking sector activity are often only available semi-annually or annually. During the gradual build-up phase quarterly signals seem to be sufficient, which may not be the case for signalling a prompt release if bad times materialise quickly.

The performance of different conditioning variables

As a first step, we analyse the performance of different conditioning variables by visually inspecting their evolution around historical banking crises. We consider the variables measured as deviations from a long-term trend or average, in order to identify the cyclical component. We do not yet superimpose a specific adjustment factor, linking the conditioning variable to the target. To illustrate the main message, the graphs in the text relate only to a subsample of the countries and variables evaluated; Annex 4 contains more information for a broader range of countries. The graphs point to a number of conclusions.

First, business and financial cycles are related, but fluctuations in output have a higher frequency than those of financial cycles associated with serious financial distress (Graph III.1 above). Episodes of financial distress are rare and reflect longer and larger cycles in credit and asset prices.

Second, aggregate credit growth and the credit-to-GDP ratio perform well in anticipating bad times, rising strongly before strains materialise (Graph III.2). In particular, the credit-to-GDP ratio tends to rise smoothly well above trend before the most serious episodes. However, neither of the credit measures is able to signal the release phase appropriately, be it in terms of timing or intensity. In a number of cases, the variables decline too late and too slowly, lagging the emergence of serious financial stress. The current crisis is the clearest example.

Third, deviations of property prices from trend can help to identify the build-up phase (Graph III.2). However, the deviations tend to narrow long before financial strains emerge, suggesting that they would start releasing the buffer too early.

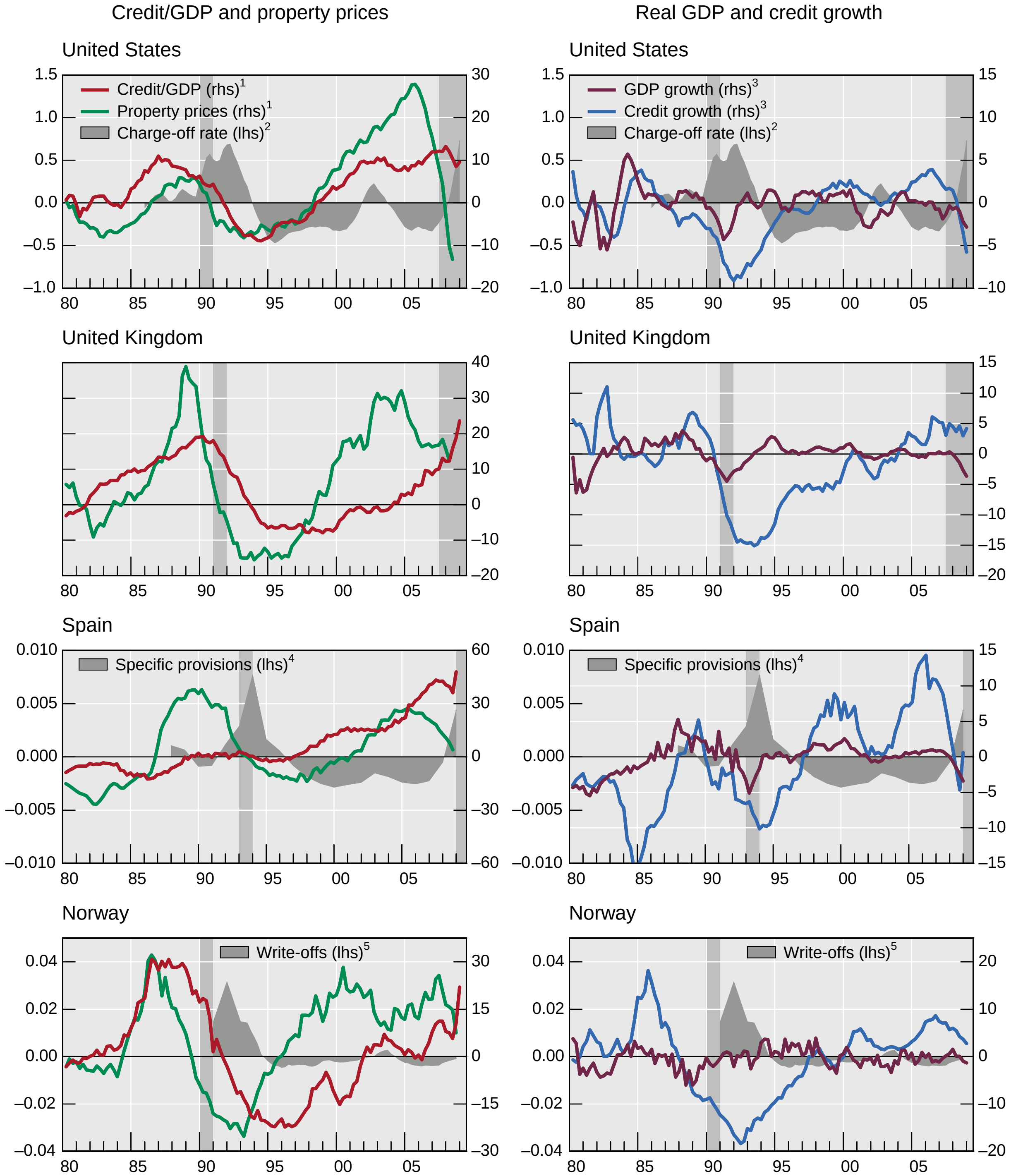
Fourth, the performance of bank (pre-tax) profits as a signal for the build-up in good times appears to be somewhat uneven (Graph III.3). The variable works very well for the United States and United Kingdom in the current crisis and for Spain in the early 1990s. It performs poorly otherwise. In the more recent experience in Spain this may be due in part to changes in accounting practices, including the introduction of dynamic provisioning; at least this effect would need to be filtered out in the analysis. In the United States in the early 1990s it reflects the fact that aggregate pre-tax profits actually increased through the period of stress, even as charge-offs surged.

Fifth, as expected, the performance of proxies for (gross) bank losses is not very satisfactory in good times (see Annex 4). The reason is that they fail to differentiate in good times, which would tend to call for very high targets early on in the expansion.

Finally, measures of the cost of funding perform well in the current crisis: they are below their long-term average ahead of it and rise very quickly as strains emerge (Graph III.4 and Annex 4). However, the performance of spreads over multiple cycles is less satisfactory, which can only be assessed for credit spreads. For the US, for example, they would have treated the episode around the 2001 recession as worse than that in the late 1980s to early 1990s. Equally, spreads would have called for a more sustained and larger build-up in the buffer in the mid 1990s than would have been the case before the current crisis.

Graph III.2

Aggregate conditioning variables: macroeconomic variables



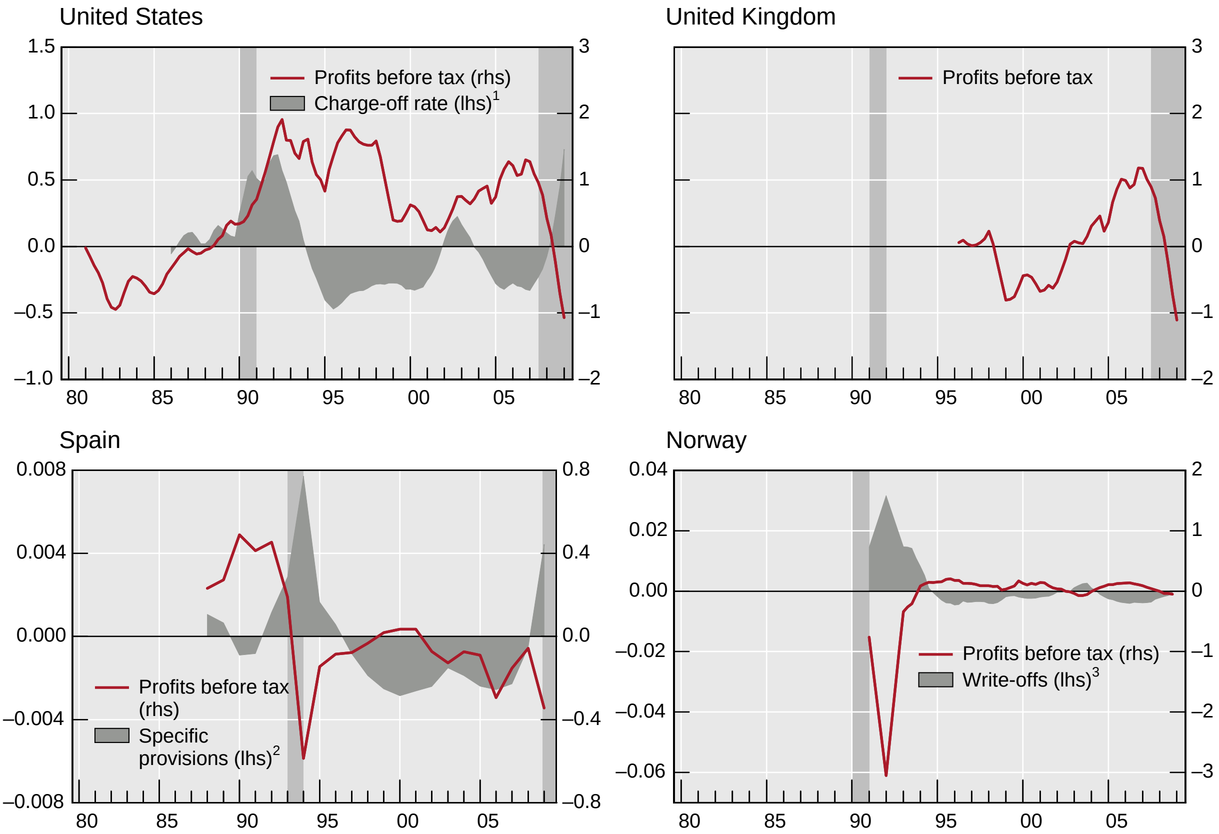
The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

[1] Deviation of each variable from its one-sided long-term trend (that is, a trend determined only from information available at the time assessments are made) using a very high value of the smoothing parameter; credit/GDP ratio in percentage points; property prices in per cent. [2] Loans and leases removed from the books and charged against loss reserves as a percentage of average total loans. Deviations from their 15-year rolling average. [3] Four-quarter average real growth minus its 15-year rolling average, in percentage points. [4] Flow of specific provisions as a percentage of total assets. Deviations from their 15-year rolling average. [5] Write-offs of loans and guarantees as a percentage of total assets. Deviations from their 15-year rolling average.

Sources: National data; BIS calculations.

Graph III.3

Aggregate conditioning variables: bank profitability



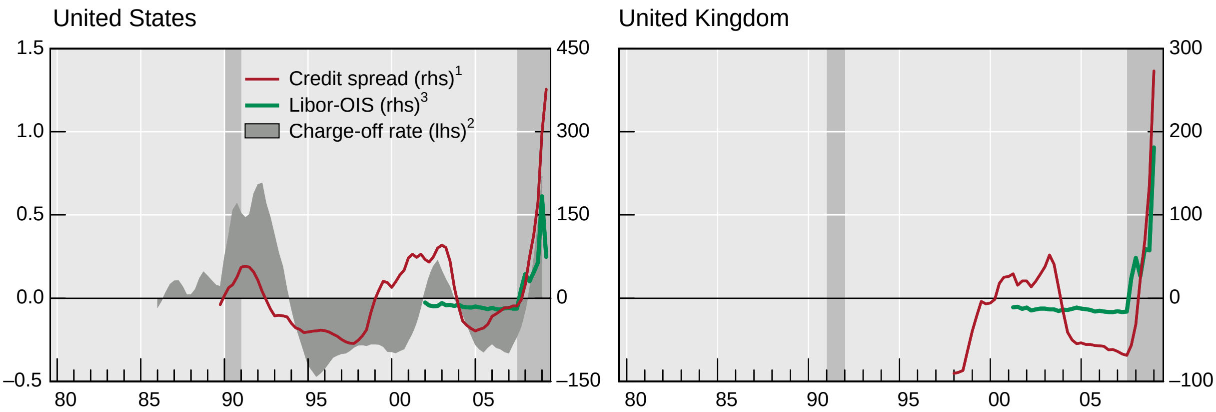
The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

[1] Loans and leases removed from the books and charged against loss reserves as a percentage of average total loans. Deviations from their 15-year rolling average. [2] Flow of specific provisions as a percentage of total assets. Deviations from their 15-year rolling average. [3] Write-offs of loans and guarantees as a percentage of total assets. Deviations from their 15-year rolling average.

Sources: National data; BIS calculations.

Graph III.4

Aggregate conditioning variables: cost of funding



The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

[1] BBB medium-term (7-10 years) corporate bond spreads; four-quarter rolling average minus its 15-year rolling average, in basis points. [2] Loans and leases removed from the books and charged against loss reserves, as a percentage of average total loans. [3] Three-month interbank rates minus three-month overnight index swaps, in basis points.

Sources: Merrill Lynch; national data; BIS calculations.

Some statistical tests

In this section we assess the performance of different variables as conditioning variables for the accumulation phase. Following the literature on early warning indicators for systemic banking crises (eg Kaminsky and Reinhart (1999)), we use a signal extraction method to provide a statistical assessment. For each period, t, a signal, S, is calculated. The signal takes either the value of 1 (is "on") or is 0 (is "off") otherwise. For variables which are "high" during boom times (such as profits or credit growth), the indicator is on if the variable exceeds a critical threshold. The opposite is the case for variables, such as spreads, which are "low" during booms. These take the value of 1 if the variable is below a specific threshold. A signal of 1 (0) is judged to be correct if a crisis (no crisis) occurs any time within a three-year horizon. Hence, we consider a flexible horizon as in Borio and Lowe (2002). While the build-up of vulnerabilities can be detected, the timing of the eruption of the crisis is unpredictable and therefore a fixed lead-lag relationship between conditioning variables and the beginning of the crisis does not apply. Signals issued in the first two years after a crisis emerged are not considered. Therefore the analysis does not enable any conclusions to be made about the performance of different indicator variables during the release phase.

We assess a range of thresholds for each indicator variable. In most cases, type 1 errors (no signal is issued and a crisis occurs) and type 2 errors (a signal is issued but no crisis occurs) are observed. Both error types are jointly summarised by the noise-to-signal ratio, which is the ratio of the fraction of type 2 errors over 1 minus the fraction of type 1 errors.

In the literature, the best early warning indicator is generally chosen on the basis of the lowest noise-to-signal ratio (eg Kaminsky and Reinhart (1999)). However, Borio and Drehmann (2009) and Alessi and Detkens (2009) point out that this may not be ideal from a policy perspective. The reason is that policymakers may assign more weight to the risk of missing crises (type 1 error) than calling those which do not occur (type 2 error) as the costs of the two differ. Given the preferences of policymakers are unobservable, Borio and Drehmann (2009) suggest minimising the noise-to-signal ratio subject to predicting a minimum percentage of crises. Green cells in Tables III.2 to III.3, therefore, highlight thresholds for which at least two thirds of crises are predicted. The red cells indicate the lowest noise-to-signal ratio, given that this condition is satisfied.

In particular for macroeconomic series, the statistical tests are based on more data than shown in the previous exercises. The analysis for the credit-to-GDP ratio, real credit growth and real GDP growth is based on 36 countries covering 25 crises.[19] Data start for most countries in 1980. Fewer data are available for property prices, indicators of banking conditions or funding spreads. Given a lack of a sufficient number of countries and\or sufficiently long series Libor-OIS spreads and CDS prices are not analysed.

Looking across the tables, we see that the credit-to-GDP gap achieves the lowest noise-to-signal ratio (20%), while still capturing more than two thirds of the crises in our sample. The property price gap also performs very well.[20] However, data on property prices are much harder to obtain. Therefore, we have only information for 15 crises. And for many countries no information is available at all, suggesting that this indicator variable would not be ideal, as it could not be easily implemented worldwide.

Profits before tax are not well suited as indicator variable to guide the capital accumulation. There is clearly a small sample issue, but the noise-to-signal ratio is generally high. This means that high level of profits are not only achieved in the run-up to crises but more generally during normal times. This is also supported by Graph A4.5 in Annex 4.

Even though they should not be overemphasised because of very small samples, the results for the spread series and also for credit losses are very striking: The change from predicting no crises to capturing all occurs very rapidly. At the same time, noise-to-signal ratios are very high. In essence, this means that during normal and boom times these indicator variables do not seem to fluctuate much (see also Graphs A4.7 to A4.9). Hence, these series are unable to provide useful signals about the intensity of the build-up of systemic risk. However, the graphs as well as the statistical tests indicate that they may be useful indicators for the release time as these variables can provide timely signals when strains emerge.

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[19] The sample consists of all G20 member countries and OECD countries, excluding transition economies.

[20] Borio and Drehmann (2009) find that early warning indicators that combine information from the credit-to-GDP gap and the property as well as equity price gap perform best. However, considering multiple variables to guide the accumulation of capital buffers is problematic as it dramatically increases the complexity of linking indicator variables to capital buffers.

Table III.2

The performance of macroeconomic conditioning variables

Threshold[1]	Type 1 error[2]	Type 2 error[2]	Predicted[2]	Noise-to-signal ratio[2]	# crises[3]	# countries[3]
Credit-to-GDP ratio[4]						
0	8	56	92	61	25	36
1	8	50	92	54	25	36
2	8	43	92	47	25	36
3	16	38	84	45	25	36
4	20	33	80	41	25	36
5	24	29	76	38	25	36
6	24	25	76	33	25	36
7	28	22	72	30	25	36
8	28	19	72	26	25	36
9	28	16	72	23	25	36
10	28	15	72	20	25	36
11	36	13	64	20	25	36
12	48	11	52	21	25	36
13	56	10	44	22	25	36
Credit growth[4]						
1	3	80	97	82	30	36
2	7	75	93	81	30	36
3	7	70	93	75	30	36
4	10	64	90	71	30	36
5	10	58	90	64	30	36
6	13	51	87	59	30	36
7	17	45	83	54	30	36
8	20	40	80	49	30	36
9	30	34	70	49	30	36
10	33	30	67	45	30	36
11	37	26	63	42	30	36
12	40	23	60	38	30	36
13	43	20	57	35	30	36
GDP growth[4]						
0.5	4	84	96	87	28	36
1	4	79	96	82	28	36
1.5	4	74	96	77	28	36
2	7	69	93	74	28	36
2.5	11	62	89	70	28	36
3	18	56	82	68	28	36
3.5	18	50	82	60	28	36
4	32	42	68	62	28	36
4.5	39	36	61	59	28	36
5	43	31	57	55	28	36
Property prices[4]						
2	13	47	87	55	15	11
4	20	43	80	53	15	11
6	20	39	80	48	15	11
8	20	34	80	42	15	11
10	20	29	80	36	15	11
12	33	25	67	37	15	11
14	33	20	67	30	15	11
16	33	17	67	26	15	11
18	33	15	67	22	15	11
20	40	12	60	20	15	11
22	40	8	60	14	15	11
24	60	5	40	11	15	11

Note: [1] Signal of 1 is issued if conditioning variable is larger than the threshold. [2] A signal of 1 (0) is judged to be correct if a crisis (no crisis) occurs any time within a three year horizon. Type 1 error: no signal is issued and a crisis occurs. Type 2 error: a signal is issued but no crisis occurs. Predicted: fraction of crises predicted by correct signals. Green cells: more than two thirds of crises are captured. The noise-to-signal ratio: fraction of type 2 errors over one minus type 2 errors. Red cells: Lowest noise-to-signal ratio given two thirds of crises are predicted. In percent. [3] Number of crises and countries in the analysed sample. Crises are not observed in all countries, but some countries have had more than one crisis. [4] GDP and credit growth are measured in real terms. Property prices and the credit-to-GDP ratio are deviations from a long run trend. In percent.

Source: National data; BIS calculations.

Table III.3

The performance of funding cost and banking sector activity indicators

Threshold[1]	Type 1 error[2]	Type 2 error[2]	Predicted[2]	Noise-to-signal ratio[2]	# crises[3]	# countries[3]
Profits before tax[4]						
0	0	98	100	98	5	6
0.5	0	68	100	68	5	6
1	20	49	80	62	5	6
1.5	40	33	60	55	5	6
2	40	29	60	48	5	6
2.5	40	25	60	42	5	6
3	60	24	40	61	5	6
3.5	60	24	40	60	5	6
4	60	19	40	46	5	6
Credit losses[4]						
0	100	6	0		7	8
0.5	29	55	71	76	7	8
1	14	80	86	93	7	8
1.5	14	86	86	100	7	8
2	14	90	86	104	7	8
Credit spreads[5]						
50	80	8	20	42	5	6
75	60	15	40	37	5	6
100	40	38	60	63	5	6
125	0	55	100	55	5	6
150	0	64	100	64	5	6

Note: [1] For profits before tax: signal of 1 is issued if profits before tax are *larger* than the threshold. Credit losses and credit spreads: signal of 1 is issued if series are *smaller* than threshold. [2] A signal of 1 (0) is judged to be correct if a crisis (no crisis) occurs any time within a three-year horizon. Type 1 error: no signal is issued and a crisis occurs. Type 2 error: a signal is issued but no crisis occurs. Predicted: fraction of crises predicted by correct signals. Green cells: more than two thirds of crises are captured. The noise-to-signal ratio: fraction of type 2 errors over one minus type 2 errors. Red cells: Lowest noise-to-signal ratio given two thirds of crises are predicted. In percent. [3] Number of crises and countries in the analysed sample. Crises are not observed in all countries, but some countries have had more than one crisis. [4] Profits before tax and credit losses are relative to total assets. Credit losses are either measured by non-performing loans, charge-offs, write-offs or specific provisions. In percent. [5] BBB medium-term (7-10 years) corporate bond spreads. In basis points.

Source: Merrill Lynch; National data; BIS calculations.

The results provide valuable information about the performance of different variables. However, we need to keep two caveats in mind. First, we assess the signalling qualities of domestic indicators for all systemic banking crises. In particular, during the recent crisis, some banks failed because of their foreign lending and not so much because domestic vulnerabilities crystallised. This was, for example, the case in Germany and Japan. Borio and Drehmann (2009) show how this signalling problem can be partially addressed by using the BIS international banking statistics, which provide information on aggregate cross-border exposures for many countries. They find that doing so improves the qualities of their early warning indicator ahead of the current crisis.

Second, a statistical type 2 error is not necessarily a type 2 error from a policy perspective. As can be seen from the graphs, it is often the case that the conditioning variable indicates the build-up of vulnerabilities more than three years before a crisis. In the statistical analysis, such a signal would be counted as false even though it would have essentially provided the right information, but just too early. There are also instances where severe banking strains were observed but no crisis was formally recorded. 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. But even with this broader view on false signals, no conditioning variable provides perfect signals. This means, that in practice, a perfectly rules based schemes seems not possible at this state. Some form of discretion to manage countercyclical capital buffers may prove to be inevitable. Nonetheless, the empirical analysis shows that suitable conditioning variables can be found. The credit-to-GDP ratio seems to be preferable for the build-up phase. Some measure of aggregate losses, possibly combined with indicators of credit conditions, seems best for signalling the beginning of the release phase. Whether and how to guide the pace and intensity of the release is less clear.

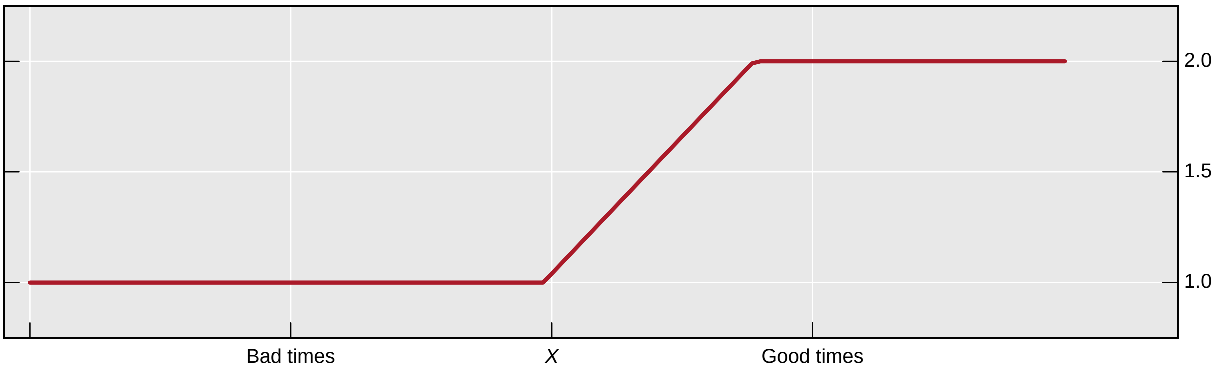
Choosing the adjustment factor

Any rule determining the build-up and release of capital buffers requires a formula linking the conditioning variable to the adjustment factor. In principle, a multitude of options are available. As outlined in the introduction, the adjustment factors considered here are multiplicative, which preserves the cross-sectional differentiation of credit risk. And they are never lower than 1, so that capital is prevented from falling below the minimum.

Given these constraints, we use the simplest functional form (Graph III.5).[21] When the indicator variable is below level X, the adjustment factor is 1. For an ideal conditioning variable, this would coincide with bad times. In good times, the target is above the minimum, and the gap rises as the conditioning variable moves away from X. The formula for the adjustment factor in this region is linear in the conditioning variable. We also impose a maximum, in order to avoid the build-up of unrealistically high levels of capital.

Graph III.5

Formula for the adjustment factor[1]



[1] The adjustment factor is 1 when the indicator variable is below some level *X* which coincides with bad times.

Source: BIS calculations.

For purely illustrative purposes, the adjustment factors in this paper are calibrated such that they equal 1 if the indicator variable is more than one standard deviation (std) below its long term average. The slope of the linear formula is 1/(2*std).[22] This implies that the target level

[21] Different functions have implications for the speed and size of the change in the adjustment factor. However, it is often possible to find a linear specification with broadly similar properties.

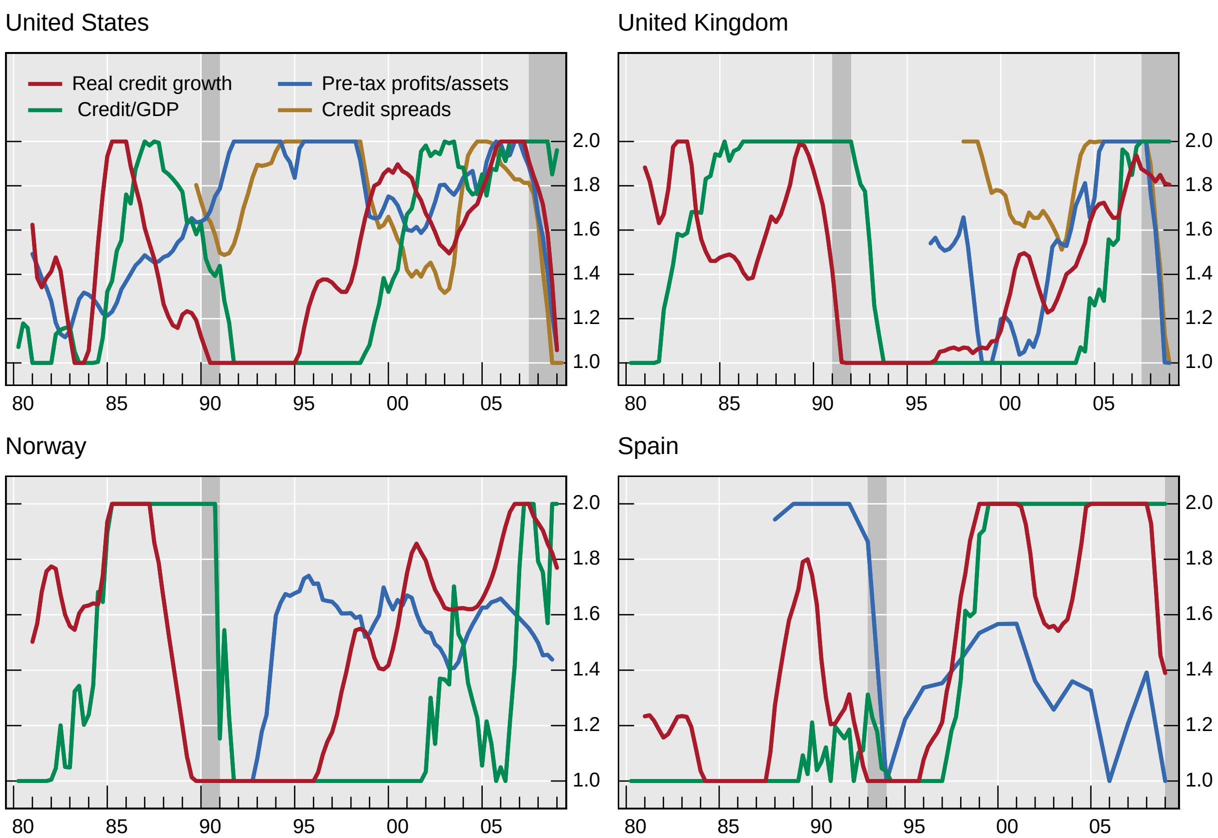
[22] The functional forms is calibrated slightly differently when credit spreads are used as conditioning variable, as credit spreads are not symmetric around the mean, and good times are indicated by compressed and bad times by high spreads. In this case, alpha equals 1 if credit spreads are more than 1.5 std above their long run

of capital is 50% above minimum when the indicator variable is at its average. For this study, the maximum for the adjustment factor is set arbitrarily at 2. Clearly, both the average and the ceiling would have to be calibrated according to the desired safety margin. The variables considered are credit growth, the ratio of credit to GDP; a credit spread and the banks' pre-tax profits-to-total assets ratio.

The results illustrate more concretely the previous conclusions in terms of the relative performance of the conditioning variables (Graph III.6 and Annex 4). They show that the adjustment factor chosen as applied to the credit variables generally succeeds in calling for a build-up of buffers to the maximum permitted before the most serious episodes of financial stress, notably the current one and that in Scandinavia in the late 1980s. There are, however, some differences in the timing of the build-up across these episodes. Likewise, the adjustment based on the credit growth variable is generally more responsive to short-term fluctuations in economic activity and bank losses. For example, in contrast to the credit-to-GDP ratio, it allows for a partial release of the buffer in 2001.

Graph III.6

Top-down approaches:
Behaviour of the adjustment factor, alpha[1]



The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

[1] Alphas are based on a linear formula. Specifications are given in the notes to the graphs in Annex 4.

Source: BIS calculations.

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average. The slope is 1/(2*std). For the credit to GDP gap, alphas equal 1 if the gap is negative and the slope is 1/10.

Comparing top-down and bottom-up approaches

How do bottom-up schemes perform compared with top-down ones? Graph III.7 provides some clues, by presenting the behaviour of asset growth for the top ten banks in the United Kingdom, for the top eight banks and banking groups in Norway and for five large banks in Spain as well as the ratio of pre-tax profits for the same institutions, except for those in Spain. All the variables are measured as deviations from the bank-specific long-term average. Graph III.8 translates these patterns into the evolution of the target above the minimum, using the same adjustment factors as in the top-down analysis. More detailed results are presented in Annex 5.

The evidence indicates that the idiosyncratic component can be substantial.[23] There is a wide dispersion in the behaviour of asset growth rates and profits. This would imply large differences in the values of the adjustment factors and in the direction of the change in the target.

In addition, it suggests that the persistence of bank-specific variables is rather low – no doubt another reflection of the importance of idiosyncratic factors (see, eg highlighted banks in Graph III.7-III.8) This is especially evident for asset growth. Even at the yearly frequency, the target would sometimes have to change direction in several successive periods.

While not shown for the sake of brevity, similar results emerge if one considers a combination of top-down and bottom-up approaches. Specifically, the individual adjustment factors are scaled up or down compared to the system-wide factor depending on deviations of individual banks from the system-wide average.[24] Here, too, there is evidence of a high idiosyncratic component and of low persistence.

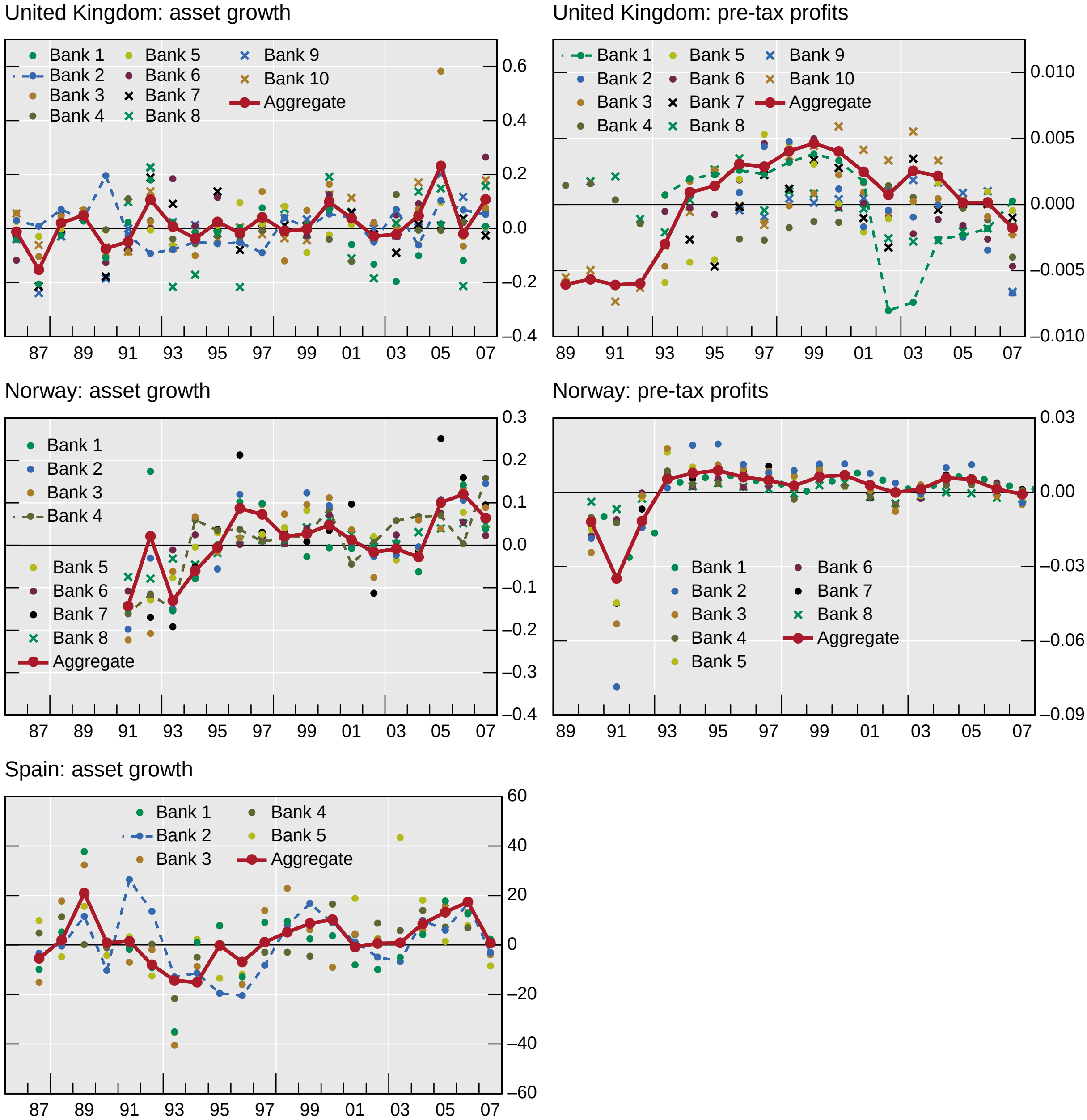
In some respects these findings are not fully comparable with those of the pure top-down approaches discussed above. Asset growth is not quite the same as credit growth. And the micro data refer to consolidated balance sheets, including foreign operations, if any. Both of these factors may induce additional sources of volatility. Even so, to the extent that they are representative, they support the view that bank-specific variables may be inferior to aggregate ones. The substantial cross-sectional and time-series variability in the adjustment factors fits uneasily with an exercise primarily designed to address a *system-wide* problem. The greater scope to arbitrage away bank-specific schemes reinforces this conclusion.

[23] Some of the fluctuation may also be driven by data problems due to, for example, mergers, large acquisitions or accounting changes, which could not be fully controlled for.

[24] For consistency, the system-wide measure is calculated by aggregating the bank-specific variables.

Graph III.7

Bottom-up approaches:
Bank-specific conditioning variables: asset growth and profits[1]

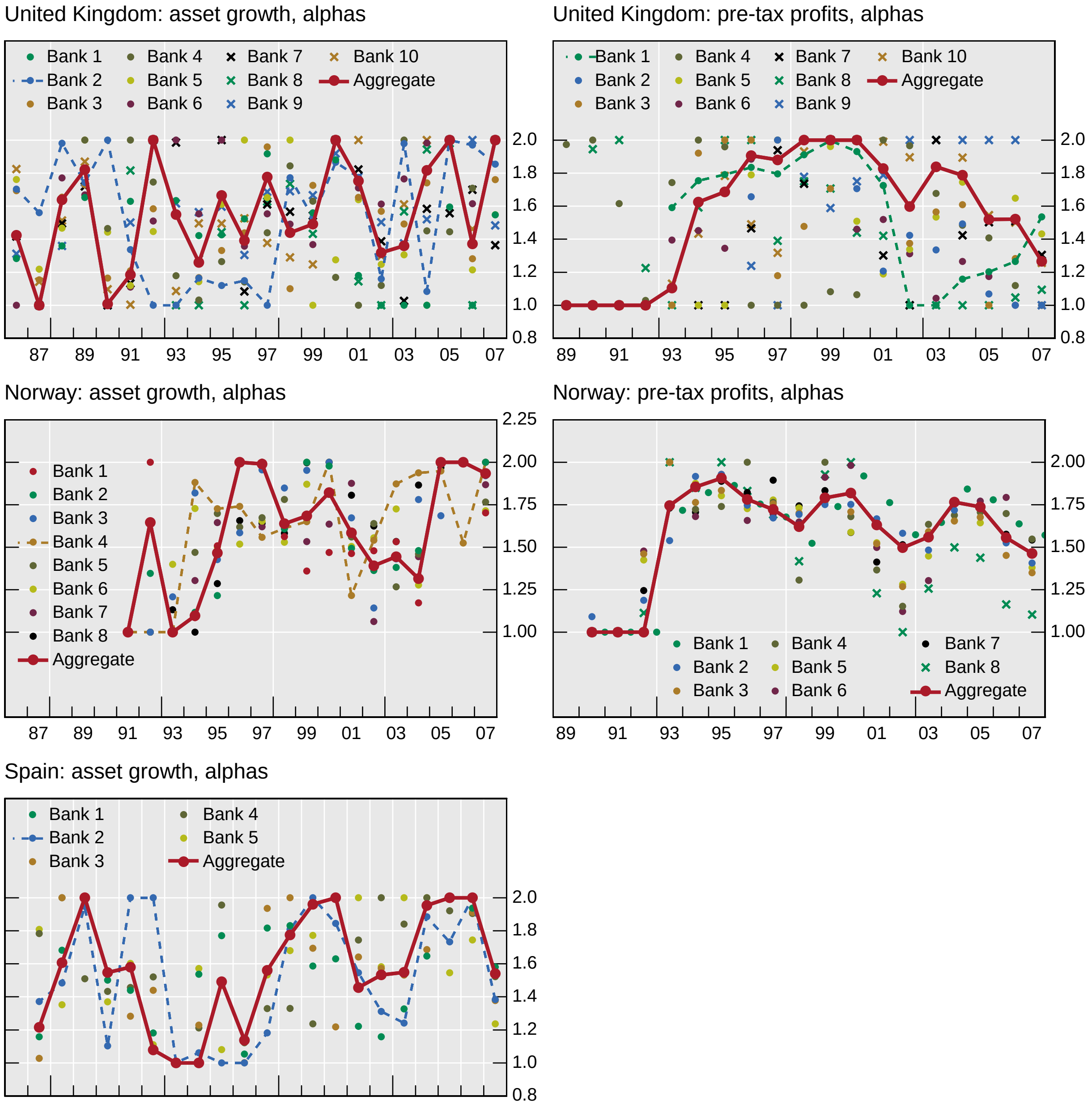


[1] Deviation from bank-specific 15-year rolling average, for aggregate series its 15-year rolling average is used. Data are based on consolidated bank balance sheets. The aggregate is based on the sum of the banks shown.

Source: Bankscope; national data; BIS calculations.

Graph III.8

Bottom-up approaches:
Behaviour of the adjustment factor, alpha[1]



[1] The adjustment factors alpha are based on a linear formula. Alpha equals 1 if the bank-specific conditioning variable is more than one (bank-specific) standard deviation (std) below its 15-year rolling average. The maximum adjustment is 2. The slope of the linear formula is 1/(2*std). Alphas for the aggregate series are based on the rolling average and standard deviation of the aggregate series.

Source: Bankscope; national data; BIS calculations.

IV. Cyclical sensitivity in minimum capital requirements

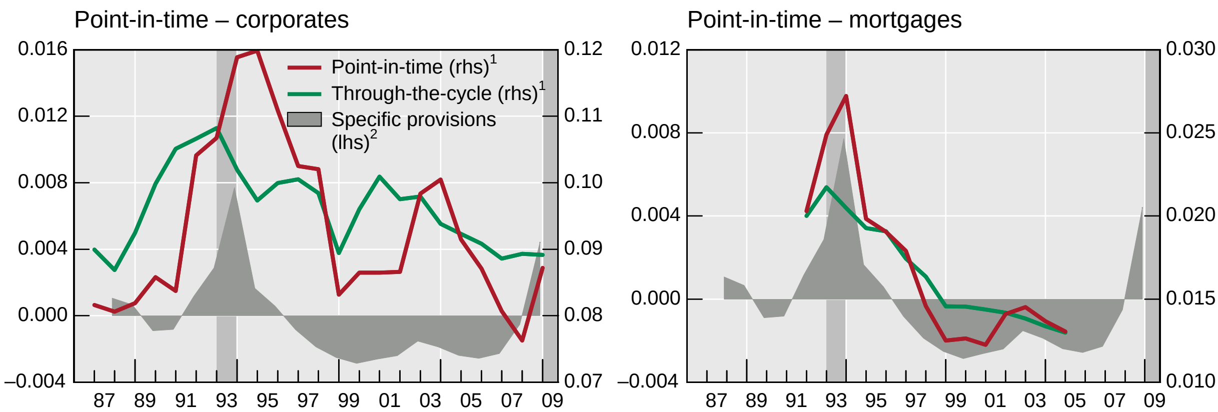
The degree of cyclical sensitivity in the minimum capital requirement is a critical element in the calibration of the schemes. The higher the sensitivity, the larger will the buffer have to be before strains emerge and the faster will the target have to fall once they arise. At worst, if the variability is substantial, it can seriously undermine the effectiveness of the schemes.

Unfortunately, the information available on the sensitivity of the minimum capital requirement is limited. Therefore, we can illustrate the issues involved only by drawing on analysis by the Bank of Spain. This simulates the behaviour of the Basel II minimum requirement for the corporate and mortgage portfolios of Spanish banks (Graph IV.1), assuming both point-in-time (PIT) and through-the-cycle (TTC) probabilities of default (eg Saurina and Trucharte (2007) Repullo et al (2010)). We take these estimates and apply the adjustment factor using credit growth and the ratio of credit to GDP as conditioning variables. For purely illustrative purposes, the sum of Tier 1 and Tier 2 is used, so that the minimum requirement is 8%.

Graph IV.1

Point in time and through-the-cycle capital requirements in Spain

Difference from mean, in percentage points



The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy

[1] Simulated Basel II minimum requirement for portfolios of Spanish banks assuming point-in-time or through-the-cycle probabilities of default; in per cent of total non-risk weighted assets. [2] Flow of specific provisions as a percentage of total assets. Deviations from their 15-year rolling average.

Sources: National data; BIS calculations.

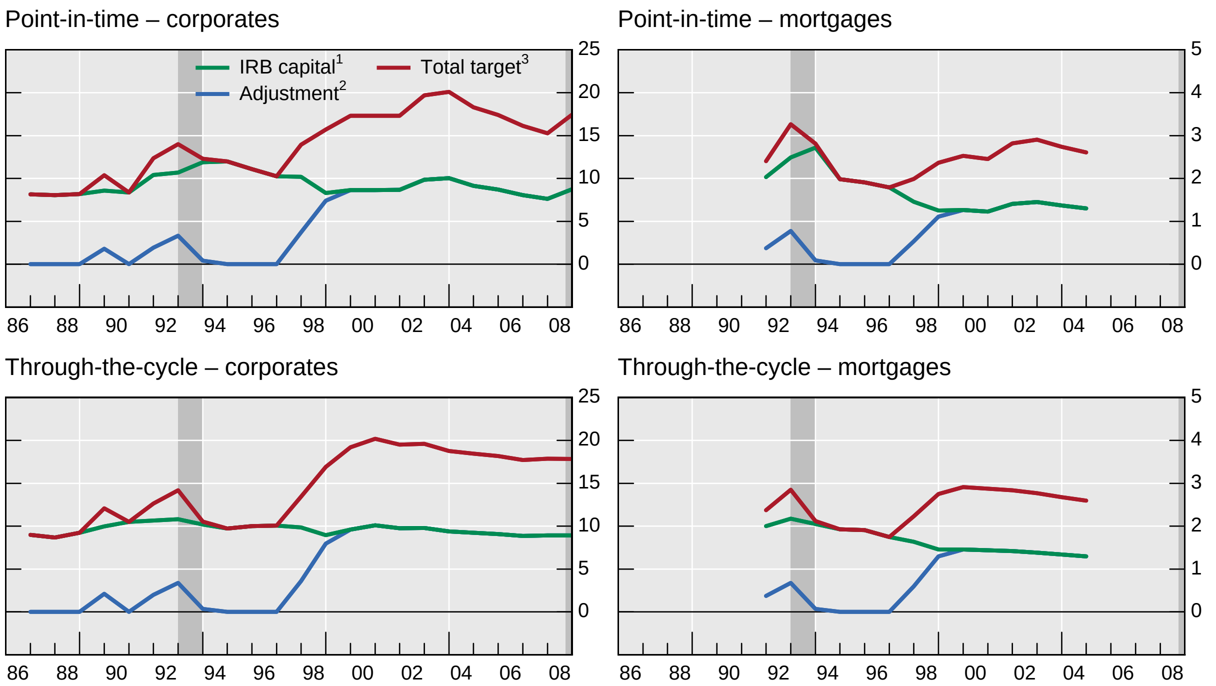
The results are shown in Graph IV.2. The two panels of the graph plot the minimum requirement, the target (minimum plus the adjustment) and the difference between the two, all as a ratio to *unweighted* assets, for the PIT and TTC variants and the two portfolio types. Unfortunately, the data for the mortgage portfolio cover a much shorter period. The vertical line corresponds to the year when serious financial strains emerged in the sample.

Importantly, the usable buffer itself *cannot* be shown, as this would require knowing the actual level of available capital above the target and hence also the losses incurred on the portfolio. To recall, *the usable buffer consists exclusively of the free capital available to absorb losses without incurring supervisory restrictions.* Only with a soft target could capital be partly used, depending on the severity of the corresponding supervisory penalties for a breach; but then one could not assume that the target shown would necessarily have been met before the emergence of the strains.

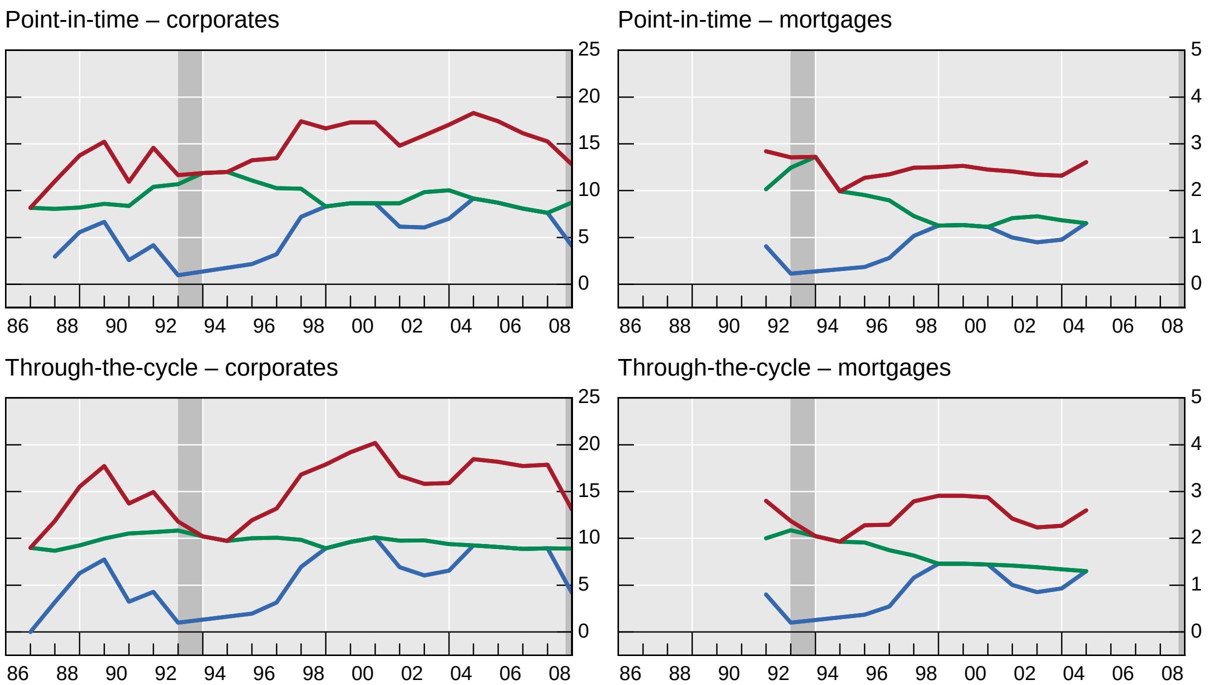
Graph IV.2

Spain: cyclical sensitivity of the minimum capital requirements: implications

Conditioning variable: Credit/GDP



Conditioning variable: credit growth



The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy

[1] Basel II minimum requirement, in per cent of total non-risk weighted assets. [2] Procyclicality adjustment given the adjustment factors shown in Graph III.1, as a per cent of total non-risk-weighted assets. [3] The target is the minimum requirement plus the adjustment, as a per cent of total non-risk weighted assets.

Sources: National data; BIS calculations.

Several points stand out.

First, the cyclical sensitivity of the PIT minimum requirement is very high (Graph IV.1). During the financial strains that started in late 1992, and which were preceded by a much more gradual deterioration in asset quality than in the present crisis, the requirement on the corporate portfolio rises from some 8% in 1990 to around 12% in 1993–94, eating heavily into available capital. Thereafter, except for a smaller increase in the economic slowdown of the early 2000s, by 2007 the requirement falls almost monotonically back to below 8%, after which it starts to rise sharply again. The cyclical sensitivity of its TTC counterpart is considerably lower, although it also exhibits a long-term decline between its peak in 1992 to 2007, from around 11% to 9%. Reflecting in part the nature of the strains and the lower risk weight, the sensitivity in the mortgage portfolio in the early 1990s measured in percentage points is somewhat lower than that of the corporate one. A trend decline is visible here too.

Second, the high cyclical sensitivity of the PIT requirements weakens the effectiveness of the scheme to build up capital buffers in good times, despite the very good performance of credit as the conditioning variable (Graph IV.2). The reason is that, once the ceiling is reached, the target naturally follows the path of the PIT minimum, declining at the same speed. This is evident in the case of the corporate portfolio, regardless of whether credit growth or the credit-to-GDP ratio is used as conditioning variable.

Finally, and less surprisingly, the cyclical sensitivity adds to the difficulties of the scheme in releasing capital sufficiently promptly and strongly (Graph IV.2). For instance, for the corporate portfolio and using the credit-to-GDP ratio as the conditioning variable, in the early 1990s the combined effect of the increase in the PIT minimum and the degree of inertia in the ratio means that the target actually rises in 1992 and declines by only a couple of percentage points in 1993, after which it changes little. Moreover, none of this takes into account the erosion in available capital that would result from actual losses on the portfolio. In contrast, the decline in the target associated with the TTC minimum between 1992 and 1993 is close to 5 percentage points.

If this picture is representative, it indicates that reducing the sensitivity of the minimum capital requirement is an important element of a credible countercyclical buffer scheme. The potentially high sensitivity of PIT requirements can weaken the effectiveness of the scheme in building up target buffers relative to unweighted assets in good times. Similarly, in bad times, it can quickly eat into the available capital resources, as the increase in risk-weighted assets adds to the erosion associated with losses.

Two implications follow. First, the target capital levels that precede the strains need to be quite high. Second, the scheme should have mechanisms in place to allow for a very quick reduction in the target once strains emerge, so as to release the buffer promptly and on an adequate scale.

V. Conclusion

The objective of countercyclical prudential capital is to encourage banks to build up buffers in good times that can be drawn down in bad times. The analysis in this paper offers a number of broad conclusions about ways in which this objective could be made more operational. They relate to the identification of what constitutes good and bad times across the cycle, as well as the suitability of different variables to act as anchors for the build-up and release phases of the scheme.

Any countercyclical capital scheme will be an overlay over the minimum capital requirements. The cyclicality of the minimum is therefore an important element for the credibility of the overall scheme. Very sensitive point-in-time capital requirements could imply that in good times risk-weighted assets decrease by so much that only limited capital is built up relative to unweighted assets. Similarly, in bad times, a highly cyclical minimum could eat into the available capital resources, as the increase in risk-weighted assets adds to the erosion associated with losses. However, it is less important whether the smoothing is achieved by adjusting inputs or outputs. In the absence of smoothing inputs, more of the work would have to be done by the adjustment factor to obtain the desired degree of capital in different stages of the cycle.

A major distinction for countercyclical capital buffers is whether conditioning variables are bank-specific or system-wide. The evidence presented in the paper indicates that the idiosyncratic component can be sizeable when a bottom-up approach is employed. This would imply large differences in the values of the adjustment factors across banks, even in times when broad financial stability pressures build up. In addition, the persistence of bank-specific factors can be very low, so that the volatility in the target for the countercyclical capital buffer could be substantial, sometimes substantially changing its size and direction in several successive periods.

For a top-down approach, the analysis shows that the best variables as signals for the pace and size of the accumulation of the buffers are not necessarily the best for the timing and intensity of the release. Credit seems to be preferable for the build-up phase. In particular when measured by the deviation of the credit-to-GDP ratio from its trend, it has proven leading indicator properties for financial distress. The corresponding data are also available in all jurisdictions, in contrast to other variables, such as CDS spreads. An additional benefit of using this conditioning variable would be that a time-varying target on credit expansion in good times could also restrain the credit boom and hence risk-taking to some extent.

Some measure of aggregate losses, possibly combined with indicators of credit conditions, seems best for signalling the beginning of the release phase. Whether and how to guide the pace and intensity of the release is less clear. In general, a prompt and sizeable release of the buffer is highly desirable as a gradual release could reduce the buffer's effectiveness.

At this stage, the conclusions of this paper should be seen as providing some initial suggestions rather than the final answer as to how countercyclical capital requirements should be implemented. Many questions remain. For example, it could be possible to construct rules based on a range of conditioning variables rather than just one. However, it is hard to envisage how this could be done in a simple, robust and transparent fashion. But our analysis indicates more generally that any fully rule-based mechanism may not be possible at this stage. As a result, some degree of judgement, both for the build-up as well as the release phase, seems inevitable.

Annex 1: The calculation of the credit-to-GDP gap

The statistical literature has analysed the properties of HP filters mainly with respect to de-trending GDP growth.[25] In general, a HP filter assumes that the original series y_t can be divided intro 2 components: the trend (g_t) and the cycle (c_t), which means $y_t = g_t + c_t$. Hodrick and Prescott (1981) propose to obtain the trend by solving the following optimisation problem:

$$\min_{\{g_t\}_{t=-1}^{T}} \sum_{t=1}^{T}(y_t - g_t)^2 + \lambda\sum_{t=1}^{T}(g_{t+1} - 2g_t + g_{t-1})^2$$

where λ (lambda) is the smoothing parameter which can be chosen. The first term in the loss function penalises the variance of the cyclical component, whilst the second puts a penalty on the lack of smoothness in the trend. Hence, the solution to the problem is a trade-off between the smoothness of the trend and how well it fits the original series.

Two solutions for this problem are well-known: If λ is zero then the optimal solution is $g_t=y_t$. If $\lambda\to\infty$, the trend converges to a linear time trend with $g_t = \beta{*}t$.

Hodrick and Prescott suggest to set λ=1,600 for quarterly data. Over the years, λ=1,600 has become the standard for business cycle analysis, when quarterly data are used. Using frequency analysis, it can be shown that this implicitly assumes a business cycle frequency of around 7.5 years.

Ravn and Uhlig (2002) analyse how λ has to be adjusted if the frequency of the data changes. They show (for the two sided filter) that it is optimal to multiply λ with the forth power of the observation frequency ratio. For example, if the frequency change is ¼ (ie from quarterly to annual), the rule implies that λ should be $(1/4)^4{*}1600$ =6.25. The argument of Ravn and Uhlig can be used to derive the λ for the credit cycle.

Empirically, the duration of business cycles ranges from 4 to 8 years in OECD countries, with a mean of around five years (see e.g. Cotis and Coppel, 2005). Far less is known about the duration of credit cycles as these have not been the focus of the literature. An indication is provided by the length between two systemic crises, which ranges from 5 years at the minimum, to nearly 20 years. The median is around 15 years. This implies that the credit cycle is between three to four times longer than the business cycle. We, therefore, assess the implication of different lambdas for the performance of the credit-to-GDP gap with :

λ= 1,600 = $1^4{*}1600$, assuming that credit cycles have the same length as business cycles

λ= 25,000 ≈ $2^4{*}1600$, assuming that credit cycles are two times as long as business cycles

λ= 125,000 ≈ $3^4{*}1600$, assuming that credit cycles are three times as long as business cycles

λ= 400,000 ≈ $4^4{*}1600$, assuming that credit cycles are four times as long as business cycles

A comparison of different choices for λ

Table A1.1 provides the results of the statistical assessment of the performance of the credit-to-GDP gap with different choices for λ. Type 1 and type 2 errors are calculated as in the main text. As an example, Graph A1.1 shows the time series of different gaps for six countries.

[25] There is a large literature analysing different statistical techniques to determine the business cycle. Canova (1998) compares for example various techniques and finds that HP filters are very good in mimicking NBER business cycles, which are derived on a more judgemental basis.

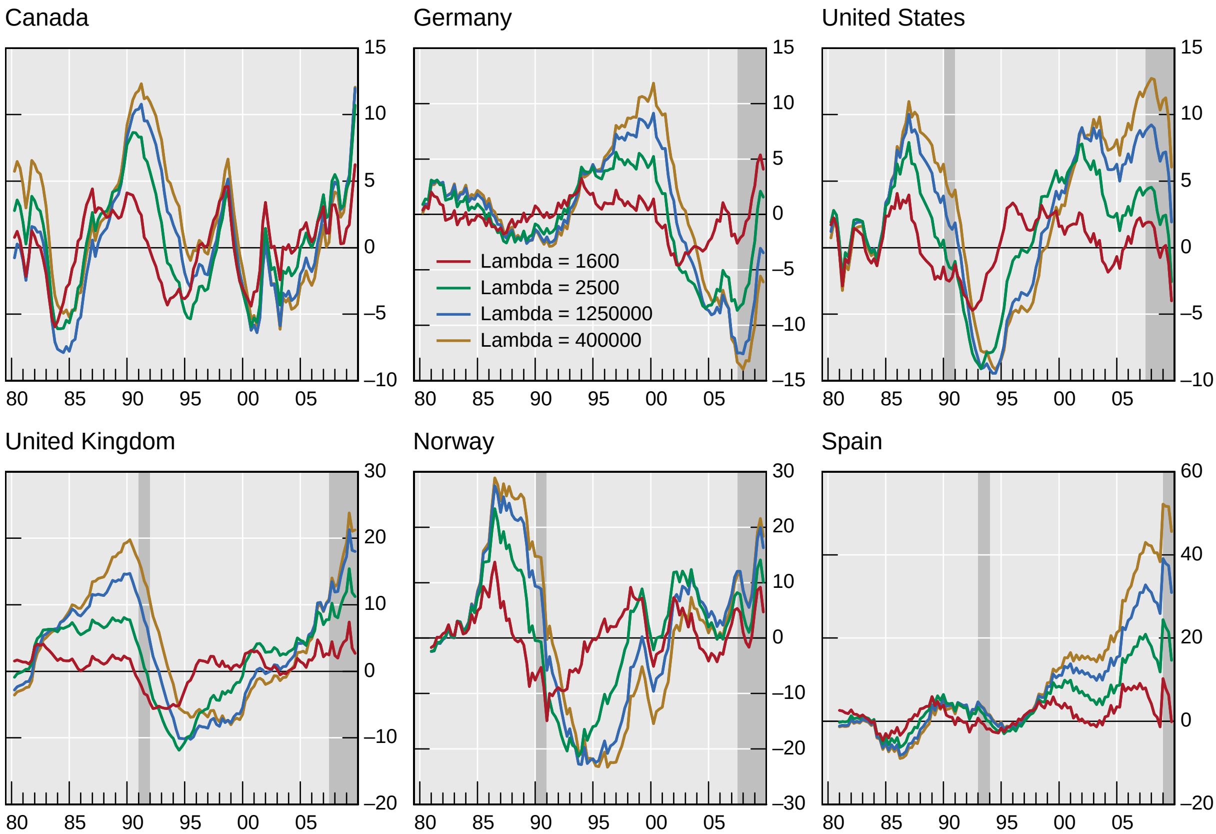
The analysis shows clearly that gaps based on λ=1600 or λ=25000 perform very poorly. This is not surprising, as the credit cycle should 3 or 4 times longer than the business cycle.

For λ=1600, the number of crises captured drops rapidly when the threshold is increased and is already below 60% for a threshold of 3. Graph A1.1also shows clearly that this gap is too volatile. The gap with λ=25000 is also relative volatile and it performs worse than the bigger lambdas for thresholds greater than 4. In addition, it drops rapidly for the US ahead of the current crises.

λ=125000 and 400000 perform both well. The higher lambda of 400000, however, implies that thresholds can be increased even further before less than two thirds of the crises are capture. This is important from policy perspective, as it provides for a greater range, and possibly more time, when the indicator variable provides strong and reliable signals.

Graph A1.1

The impact of different smoothing parameters on the credit-to-GDP gap[1]



The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

[1] The credit-to-GDP gap are the deviation from the credit-to-GDP ratio from a one-sided long-term trend (that is, a trend determined only from information available at the time assessments are made). The legend indicates the value of the smoothing parameter lambda; in per cent.

Sources: National data; BIS calculations.

Table A1.1
A comparison of different choices for λ (lambda)
in percent

Threshold[1]	Type 1 error[2]	Type 2 error[2]	Predicted[2]	Noise-to-signal ratio[2]
lambda=1600				
1	11.5	43	88.5	48.6
2	23.1	27.5	76.9	35.8
3	42.3	16.3	57.7	28.3
4	46.2	9.62	53.8	17.9
5	65.4	5.89	34.6	17
lambda=25000				
1	7.69	48.5	92.3	52.5
2	7.69	41	92.3	44.4
3	7.69	33.3	92.3	36.1
4	19.2	26.1	80.8	32.3
5	30.8	19.4	69.2	28.1
6	38.5	15.1	61.5	24.5
7	42.3	10.8	57.7	18.7
8	50	8.25	50	16.5
9	61.5	6.23	38.5	16.2
lambda=125000				
1	7.69	46.2	92.3	50.1
2	15.4	39.6	84.6	46.8
3	15.4	33.8	84.6	40
4	19.2	29.1	80.8	36
5	23.1	24.8	76.9	32.3
6	23.1	20.6	76.9	26.7
7	30.8	16.5	69.2	23.8
8	30.8	14.1	69.2	20.4
9	38.5	11.7	61.5	19.1
10	38.5	9.79	61.5	15.9
11	50	8.18	50	16.4
12	61.5	6.84	38.5	17.8
lambda=400000				
1	11.5	46.4	88.5	52.5
2	11.5	39.9	88.5	45.1
3	19.2	34.5	80.8	42.8
4	23.1	30.4	76.9	39.5
5	26.9	26.5	73.1	36.2
6	26.9	23.6	73.1	32.4
7	30.8	20.4	69.2	29.5
8	30.8	18	69.2	26
9	30.8	15.3	69.2	22.1
10	30.8	13	69.2	18.8
11	38.5	11	61.5	17.9
12	50	9.69	50	19.4
13	57.7	8.32	42.3	19.7
14	61.5	7.29	38.5	19

Note: [1] Signal of 1 is issued if conditioning variable is larger than the threshold. [2] A signal of 1 (0) is judged to be correct if a crisis (no crisis) occurs any time within a three year horizon. Type 1 error: no signal is issued and a crisis occurs. Type 2 error: a signal is issued but no crisis occurs. Predicted: fraction of crises predicted by correct signals. Green cells: more than two thirds of crises are captured. The noise-to-signal ratio: fraction of type 2 errors over one minus type 2 errors. Red numbers: Lowest noise-to-signal ratio given that two thirds of crises are predicted.

Annex 2: Comparing different credit variables

Introduction

This annex compares alternative credit measures to be used as conditioning variables in a rule to build countercyclical capital buffers. The credit indicators analysed in the main text are based on statistical formulas that may not take fully account of the equilibrium level of lending given the state of the economy. We therefore compare them with a model-based measure that allows for the possibility that the equilibrium level of credit demand and supply is dependent on other macroeconomic factors. This includes the level of interest rates, which are the main channel through which banks set their lending standards.[26] In particular, we compare pure statistical measures (the growth rate of bank lending, the total credit-to-GDP ratio) with a long run economic relationship obtained from a Vector Error Correction Model (the cointegrating vector that identifies the equilibrium in the bank lending market). We perform this comparison for the US, for which sufficiently long time series are available.

The analysis shows that a credit-to-GDP gap issues the strongest signals ahead of the current crisis. This indicates that in periods of low interest rates the model-based measure would have to be corrected even further to take account of possibility of a risk-taking channel (Borio and Zhu, 2008). Given that countercyclical capital schemes should be simple and transparent, this makes the model-based measures less attractive.

Data description

The VECM is based on quarterly data for the United States over the period 1989:q1 to 2008:q4. The interaction between the credit market and economic activity is analysed by means of the following variables: bank lending to the private sector, including non-bank financial firms (c), real GDP (y), the consumer price index (p), the average lending rate (l), and the monetary policy interest rate (i).

The sample period starts from 1989 in order to avoid structural breaks problem due to the introduction of Basel I. At that date all major institutional changes that affected competition in the US credit market had already taken place (Dynan, Elmendorf and Sichel, 2005).

The real GDP and bank lending series are those compiled by the IMF. A graphical analysis of the behaviour of annual percentage changes in GDP and credit is reported in Graph A2.1. It shows a high correlation between the series suggesting the possibility that they are cointegrated. In general, better economic conditions usually increase the number of projects that become profitable in terms of expected net present value and hence increase the demand for credit (Kashyap, Stein and Wilcox, 1993).[27]

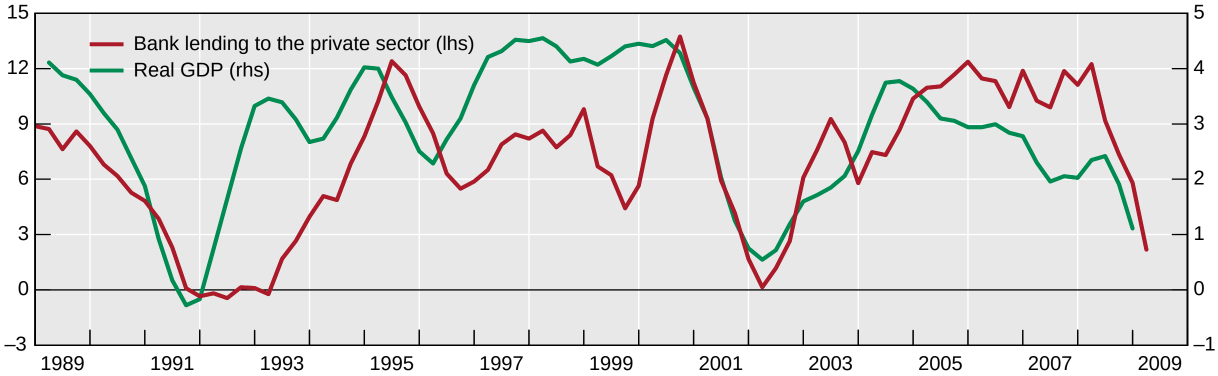
[26] Although the first empirical works on bank lending date back to the early 1930s (Tinbergen, 1937), for the next 50 years, research was devoted mainly to the study of demand for money, as credit was considered only the mirror image of monetary aggregates (Fase, 1995). Only recently a growing strand of empirical literature has been devoted to bank lending. Examples of studies on the long-run relationship between bank lending and the business cycle are reported in Kakes (2000) and Gambacorta and Rossi (2010).

[27] The sharp acceleration of bank lending to the private sector in the fourth quarter of 2008 (see Graph A2.1) is due to bank lending supplied to the financial sector while in the same period home mortgage declined for the first time in 50 years (Duke, 2009).

Graph A2.1

Bank lending and the business cycle in the United States

Annual percentage changes



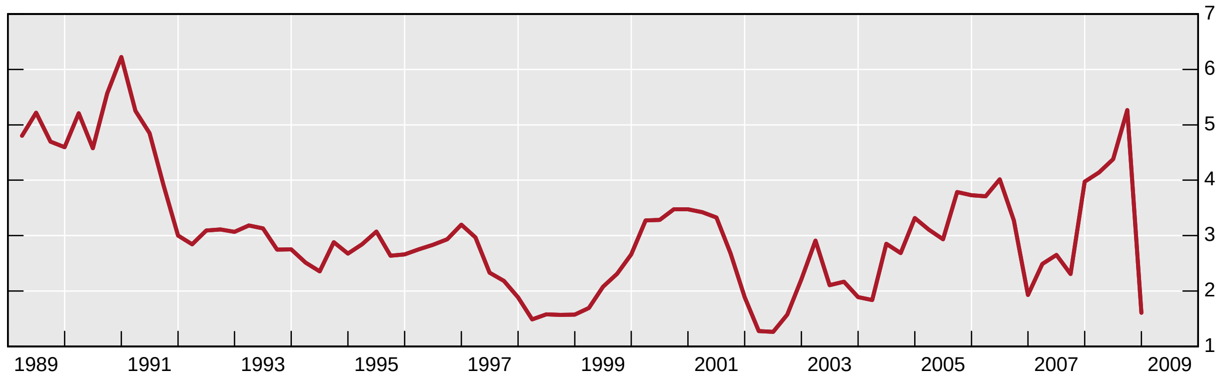
Source: IMF.

The seasonally adjusted consumer price index is calculated by the OECD. Graph A2.2 shows a sharp reduction in the last quarter of 2008 due to the drop in energy prices. Nominal lending is probably positively correlated with the price index, and the hypothesis of homogeneity between the two variables will be formally tested in the econometric analysis.

Graph A2.2

Consumer price index in the United States

Annual percentage changes



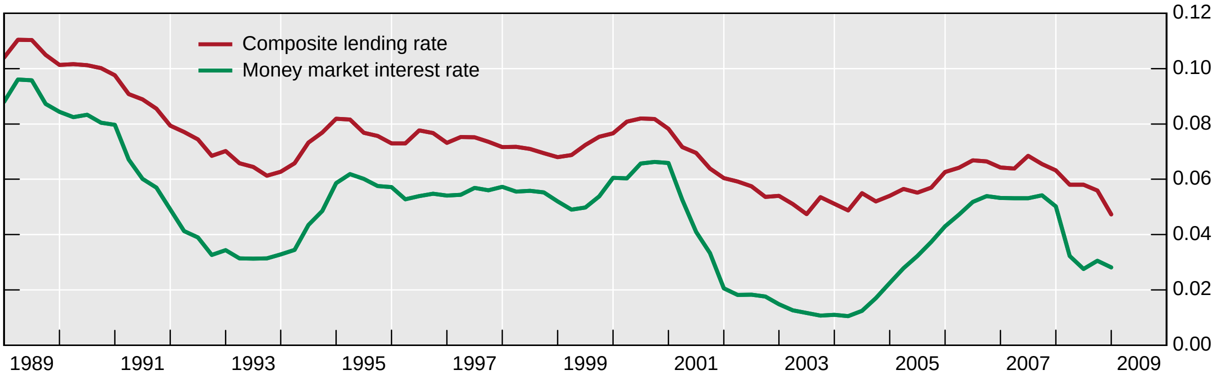
Source: OECD.

The composite lending rate is obtained by weighting bank lending rates on different types of loans (mortgage rates, commercial and industrial lending rate). The weights are given by the relative importance of the corresponding loan category. The monetary policy interest rate is proxied by the three-month interbank rate. The behaviour of the composite lending rate and of the monetary policy indicator clearly shows that the two series are cointegrated (Graph A2.3). However, it is necessary to check for the existence of a break in the difference between the two series l-i (the mark-up), which typically captures both credit risk and structural characteristics of the lending market (Graph A2.4). The mark-up tends to increase if, other things equal, borrowers become more risky (proxied by the delinquency rate in the graph).[28]

Graph A2.3

Interest rates in the United States

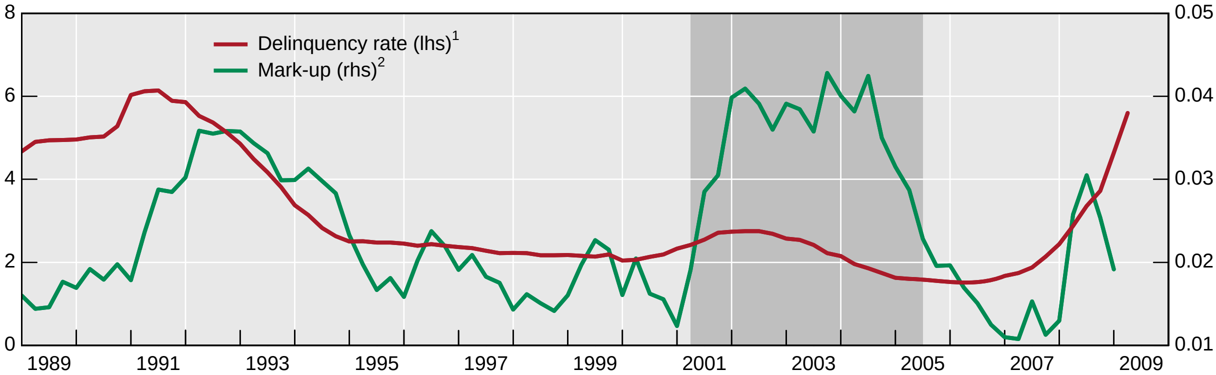
In per cent



Source: Federal Reserve.

Graph A2.4

Structural break in the mark-up



The shaded area represents a period of increase in the mark-up that it is not captured by a contemporaneous substantial increase in the delinquency rate.

[1] Given by the dollar amount of banks' delinquent loans divided by the value of total loans held in the portfolio. Delinquent loans and leases are those past due 30 days or more and still accruing interest as well as those in non-accrual status. [2] The difference between the composite bank interest rate and the monetary policy indicator.

Source: BIS calculations.

[28] The increase in the mark-up that occurred in the period 2001–2005 is not due to an increase in the delinquency rate. One possible explanation could be an increased risk-taking in connection with a period of very low nominal interest rates. In the aftermath of the burst of the dotcom bubble the Fed lowered interest rates to ward off a recession. Prior successes in taming higher levels of inflation buttressed the support for a large number of central banks to lower interest rates. As a result central banks in a significant number of developed countries kept interest rates low for a long time (Taylor, 2009). The shift in the mark-up towards a new equilibrium level in the period 2001–2005 could have been driven at least partly by an extremely low level of the short-term interest rate, probably indicating the presence of a "risk-taking channel" (Borio and Zhu, 2008).

The Vector Error Correction Model

We start with a five-variable VAR system; all the variables, that are found to be I(1) without drift, are treated as endogenous. Therefore the starting point of the multivariate analysis is:

$$
\begin{aligned}
& z_t = \mu + \sum_{k=1}^{p} \Phi_k z_{t-k} + \varepsilon_t \qquad t = 1,\dots,T \\
& \varepsilon_t \sim \mathrm{VWN}(0,\Sigma)
\end{aligned} \tag{1}
$$

where z_t=[*c, y, l, p, i*] and ε_t is a vector of residuals. The deterministic part of the model includes a constant; the number of lags (p) has been set equal to 3 based on information criteria (Akaike and Schwarz). The analysis of the system showed serially uncorrelated residuals. However, normality of the VAR is not achieved because of the presence of an outlier in the CPI equation in 2008:q4 in correspondence with the sharp decrease in energy prices described in the previous section (see Table A2.1).[29]

The I(1) nature of the variables included in z_t implies that one or more cointegrating relationships may exist. Equation (1) is then rearranged as a reduced-form error correction model:

$$
\begin{aligned}
& \Delta z_t = \Pi(\mu, z_{t-1}) + \sum_{k=1}^{p-1} \Gamma_k \Delta z_{t-k} + \varepsilon_t \qquad t = 1,\dots,T \\
& \Pi = (\Theta_1 - I) = \alpha\beta'
\end{aligned} \tag{2}
$$

where the constant is included in the cointegration space.

Table A2.1

Jarque-Bera normality tests[1]

Equation	Skewness	p-value	Kurtosis	p-value	Sk. & Kurt.	p-value
c	2.20	0.13	2.14	0.14	4.39	0.11
y	0.37	0.54	1.88	0.17	2.25	0.32
p	30.54	0.00	127.63	0.00	158.18	0.00
l	0.21	0.64	5.03	0.03	5.42	0.07
i	4.30	0.04	0.18	0.66	4.49	0.11
System	10.32	0.07	20.50	0.00	30.80	0.00

[1] Normality is accepted when the p-value is larger than 5%.

This framework can be used to apply Johansen's trace test to verify the order of integration of the matrix Π. In fact, the rank of Π determines the number of cointegrating vectors (r) such that α is an $n \times r$ matrix of loading coefficients and β is an $n \times r$ matrix of cointegrating vectors. The results (not reported for the sake of brevity) showed the presence of two

[29] The introduction of a point dummy for the fourth quarter of 2008 does normalise the system (p-value 0.23) and do not alter the long run properties of the model. However, since we are particularly interested in analysing the behaviour of the model in the light of the current financial crisis we decided not to insert the dummy.

cointegrating vectors in the model.[30] The existence of two cointegrating vectors allows us to test for the presence of a long-run relationship for bank lending quantity and among interest rates.

Bank lending should be a positive function of real GDP and prices and a negative function of the composite lending rate. In other words, we suppose the existence of a log-linear long run relationship of the type $c=\beta_{1,1}\,y+\beta_{1,2}\,l+\beta_{1,3}\,p$, in which the hypothesis of homogeneity between loans and prices may be tested for $\beta_{13}=1$.

As for interest rates, economic theory on oligopolistic (and perfect) competition suggests that in the long run the lending rate should be related to the monetary policy rate, which can proxy the cost of banks' refinancing.[31]

The mark-up is quite stationary over the sample period but it has a sudden and unexpected jump in the period 2001-2005 (see Graph A2.4). In order to control for this jump we allow the constant in the cointegrating space to assume a different value over the sub-period 2001:q1-2005:q2 (variable *dum*).

The normalized cointegrating relationships are the following (with standard error in brackets).

$$c = \underset{(0.010)}{1.276}\,y - \underset{(1.003)}{11.267}\,l + p + \underset{(0.0384)}{0.0749} \qquad (3)$$

$$l = i + \underset{(0.002)}{0.027} + \underset{(0.001)}{0.014}\,dum \qquad (4)$$

The set of over-identified restrictions, including the test for price homogeneity in the bank lending equation ($\beta_{1,3}=1$), is accepted with a p-value of 38 per cent.

As for the estimated coefficients, the long-run elasticity between lending and GDP, $\beta_{1,1}$, is equal to 1.3, which is in line with results for the euro area (Calza et al., 2006; Gambacorta and Rossi, 2010). An income elasticity above one is likely to reflect the omission of some variables from the model such as wealth or house purchases that are not captured by GDP transactions. The semi-elasticity of bank loans with respect to the composite lending rate β_2 is negative (–11.3), a value more than double that found for the euro area. As for the second cointegrating vector, the long-run equilibrium mark-up μ is equal to 2.7% but jumps to more than 4% in the 2001–2005 period.

The loading coefficients of the two cointegrating vector in the bank lending equation are respectively –0.06*** and –0.95***. This means that in the case of an exogenous shock to bank loans, the adjustment towards the new equilibrium is very slow (only 6% in the first quarter) while in the case of an exogenous shock in the mark-up the adjustment of bank lending is very fast (95% in the first quarter).[32]

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30 The asymptotic critical values of the Johansen's trace test have been calculated according to Johansen and Nielsen (1993) in order to deal with the presence of a step dummy variable in one of the long run relationship.

31 For example, Freixas and Rochet (1997) show that in a model of imperfect competition among N banks that each one sets its lending rate as the sum of the exogenous money market rate and a constant mark-up. The supply schedule is of the form $l=i+\mu$ where $\mu = \gamma_C + l'(c^*)\frac{c^*}{N}$ is constant. The mark-up μ is influenced by risk and constant marginal cost of intermediation on lending γ_C and by the elasticity of the loan demand function evaluated at the optimum (c^* is the amount of credit at the equilibrium). It is worth noting that in the case of perfect competition ($N\rightarrow\infty$) the last part of μ goes to zero and the mark-up is only influenced by marginal costs and the risk component.

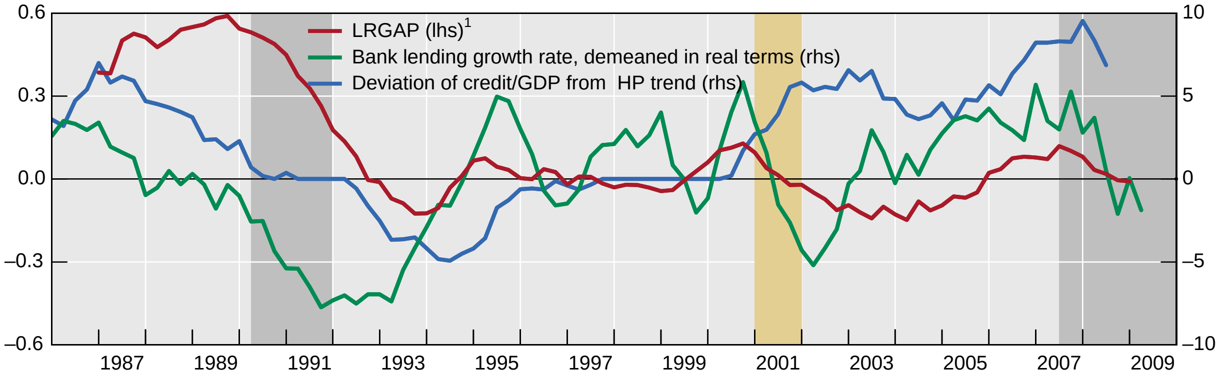
32 The robustness of the above results has been checked in several ways. First, since the long-run coefficients of the credit equation may change over time we have run again the VECM model over the period

A comparison of credit measures to use as conditioning variables

Graph A2.5 plots three credit measures that could be used as conditioning variables: (1) the deviation of bank lending from its long-run economic equilibrium value (LRGAP); (2) bank lending growth in real terms demeaned (GROWTH); (3) the deviation of the credit-to-GDP ratio from a statistical HP trend in excess of a threshold fixed at 4% (CGR). In the graph we have considered the three recession periods of the US economy in 1991, 2001 and 2008. However, only the 1991 and the current recession could be considered as periods of recession connected with a financial crisis. The "dot com" crisis (represented with a beige shaded area) was characterised by a low level of charge-offs and no significant effects on the supply of bank lending.

Graph A2.5

Comparing credit measures to build countercyclical capital buffers for banks in the United States



The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy. The beige shaded area represents just a recession period.

[1] Deviation of bank lending from its long run economic equilibrium value obtained by means of a cointegrating relationship.

Source: BIS calculations.

From the analysis of Graph A2.5 we can draw the following conclusions:

(i) The LRGAP and CGR measures seem to anticipate the occurrence of the financial crisis in 1991 and 2007 since they are in the positive area for a substantial number of quarters before the occurrence of the crisis. The measure of excessive bank lending GROWTH is not able to detect the 1991 crisis correctly while it anticipates the present one.

(ii) The LRGAP and CGR measures indicate the possibility of a capital release after the 1991 crisis. The GROWTH does not have the correct timing because the capital release would have started two years before the crisis.

1983:q1-2008:q4. The estimated long run credit equation w as the following: $c = \underset{(0.011)}{1.324}\, y - \underset{(1.230)}{15.95}\, l + p + \underset{(0.0394)}{0.0841}$ showing that coefficients were not too much different with respect to those reported in equation (3) except for the bank interest rate semi-elasticity. In this case, however, due to the presence of a structural break in coincidence with the implementation of the Basel Accord, the cointegrating rank statistic was no longer two. The introduction of a trend dummy (*t*) for the period 1983–1989 inside the cointegrating space is able to tackle this problem. In this case the long run credit equation turns out to be equal to: $c = \underset{(0.009)}{1.102}\, y - \underset{(1.12)}{8.550}\, l + p + \underset{(0.0124)}{0.0510} + \underset{(0.001)}{0.004}\, t$ with coefficients not to different with respect to equation (3).

(iii) All measures show a positive deviation before the "dot com" crisis pointing to the building up of financial distress. However, after the 2001 recession, only the CRG measure continues to signal an increase in the probability of a financial crisis while the other two measures would have allowed for a release of capital. This period of release is particularly prolonged for the LRGAP measure and could be explained by the low level of interest rates that increased the level of expected bank lending demand. In other words, the negative value of the LRGAP is probably due to the fact that even if the growth of lending was quite high in that period, loan demand was expected to be even greater. This indicates that in periods of low interest rates the measure has to be corrected to take into account the possibility of a risk-taking channel could materialise (Borio and Zhu, 2008).

All in all and taking also into account the simplicity and the low cost of calculation, the credit-to-GDP ratio seems to be most attractive conditioning variable amongst the various credit measures.[33]

[33] The CRG measure, including all forms of credit including securitisation items, suffers less of the potential statistical problems linked to the "originate-to-distribute" model of financial intermediation. A possible extension of the analysis could be to consider an economic relationship for total credit, including the interest rate on bonds when constructing the weighed interest rate.

Annex 3: Comparing different measures of bank profitability

Linking the countercyclical instrument to different measures of bank profitability and income can help to smooth the credit cycle measured more narrowly in relation to banks as opposed to the financial sector at large. Periods of high bank profitability are typically periods when banks tend to increase their intermediation activity through rapid credit growth and risk-taking. These are also periods when internal capital resources, notably retained earnings, are more easily available and when buffers can be built at a lower cost. Benign economic conditions are also associated with low realised credit costs on banks' portfolios and as such should be periods when loss absorbing cushions can be accumulated for use in more strenuous ones. We consider several measures of bank profitability:

Bank income: The sum of banks' net-interest and non-interest income tracks the earning power of banks. This variable in comparison to profits is less prone to strategic manipulation. An instrument based on bank income would act as a "tax" on banking sector activity aimed at smoothing its volatility over the cycle.

Banking sector profits: This is a key indicator of performance for the sector. Earnings increase steadily in good times and quickly reflect losses in times of stress. Profit figures, however, can be the subject of strategic management by banks that can distort their information content. A possible mitigating factor is that profits are also linked to incentives within the banks, since they determine performance-related pay, and are also under the scrutiny of analysts and shareholders. Below we consider pre- and post-tax profits.[34]

The analysis is based on the FDIC call reports for all US saving institutions and banks. Data start in 1992 and become quarterly from 2003 onwards.

Graph A3.1 provides an overview of the growth rates of the different profitability series. Taking deviations above (below) the mean as signals for good (bad) times, it is apparent that bank income is the least suitable measure. Whilst its growth rate dips below the average at the beginning of the current turmoil, it does so by roughly the same amount after the bust of the dot-com bubble. Furthermore, using income as an indicator variable would have indicated a larger build-up in the mid 1990s than ahead of the current crisis.

As banks' profits should increase when balance sheets grow, the most common way to assess the profitability of banks is to look at the return on assets (RoA) or the return on equity (RoE).[35] Using the RoE as indicator variable is problematic on conceptual grounds alone, as it mixes a profitability measure with leverage. Graph A3.2 also shows that in contrast to the RoA, the RoE would have at best marginally signalled any build-up of risks before the current crises. Comparing Graph A3.2 with Graph A3.1 it is apparent that normalising by assets rather than taking growth rates leads not only to a more intuitive but also to a better conditioning variable.

There is also a clear indication from both graphs that (post-tax) profits are smoother than pre-tax profits. This is not surprising as the former includes tax payments, provisions and extraordinary items. Given that that these items of the profit and loss account can be subject to strategic manipulation and given that the signalling content of the pre- and post-tax profit

[34] For pre-tax profits we use the FDIC series pre-tax net income which is defined as the net income (loss) before income taxes and extraordinary items and other adjustments minus gains (losses) on securities not held in trading accounts. For post-tax profits we use net income which is defined as net interest income plus total non-interest income plus realised gains (losses) on securities and extraordinary items, less total non-interest expense, loan loss provisions and income taxes.

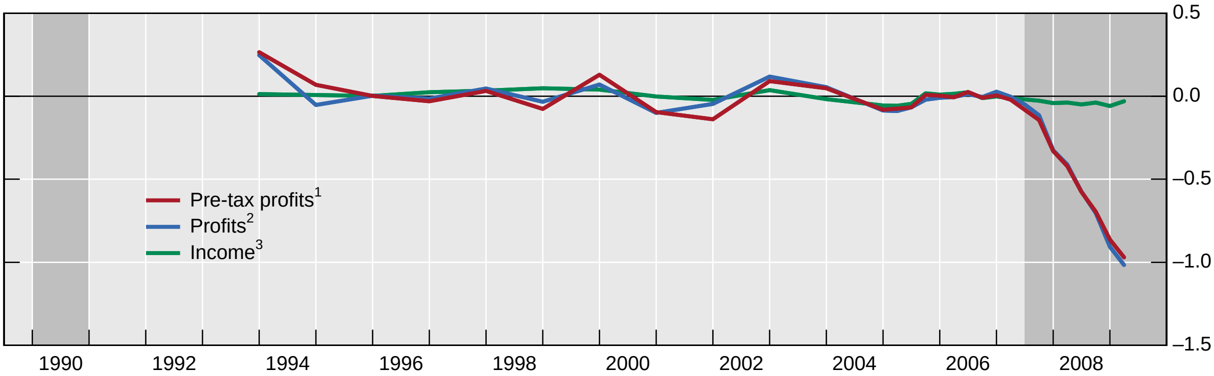
[35] We also explored the normalisation by GDP, which shows a clear upward trend. It is questionable whether this is the right approach given that banks are internationally active.

series for good and bad times is roughly similar, we conclude that pre-tax profits over total assets is the most suitable conditioning variable among profitability measures.

Graph A3.1

Real growth rates of different probability measures in the United States

Difference to mean



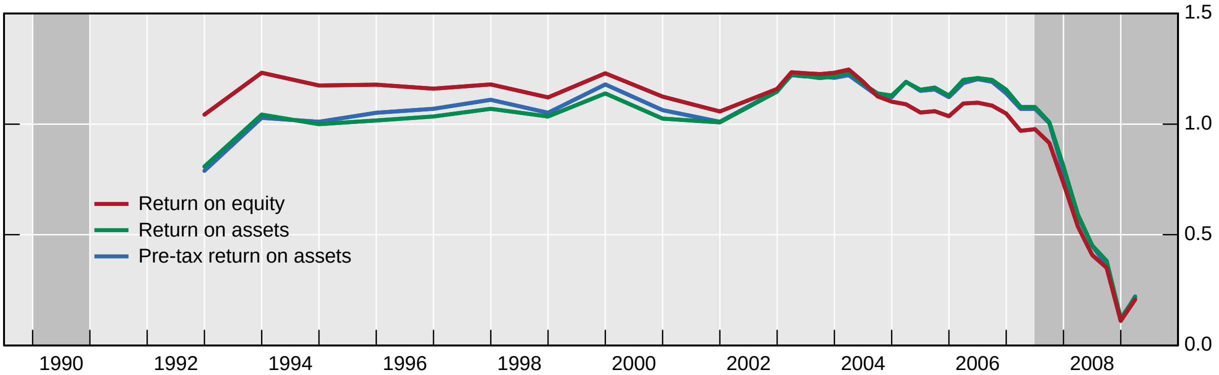
The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

[1] Net income (loss) before income taxes and extraordinary items and other adjustments minus gains (losses) on securities not held in trading accounts. [2] Sum of net interest income, total non-interest income and realised gains (losses) on securities and extraordinary items, less total non-interest expense, loan loss provisions and income taxes. [3] Sum of net interest income and non-interest income.

Source: National data.

Graph A3.2

Comparison of RoE and RoA in the United States



The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

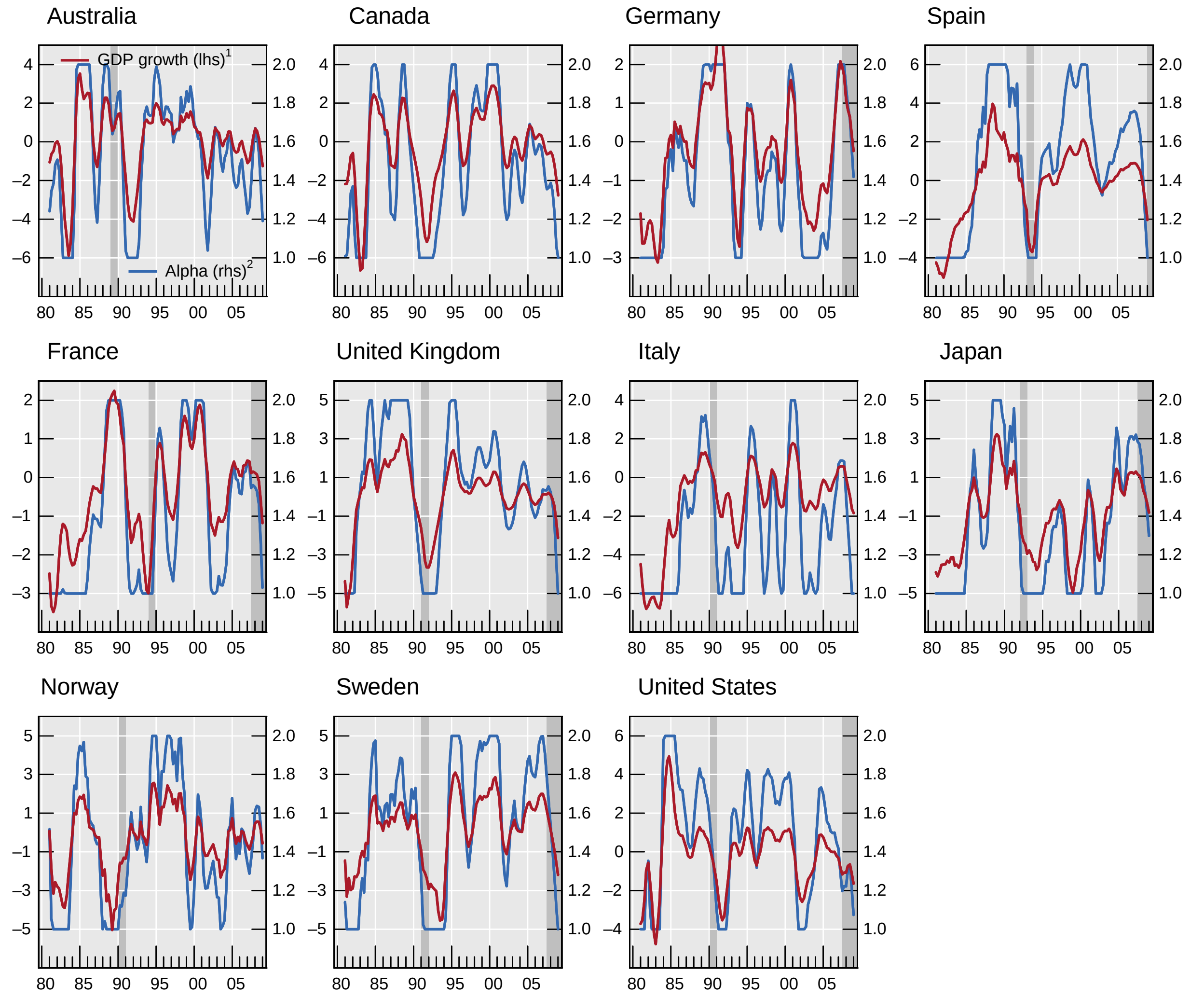
Note: To make the RoE and RoA comparable, variables are divided by their respective mean.

Source: National data.

Annex 4: Aggregate conditioning variables and the corresponding alphas

Graph A4.1

GDP growth



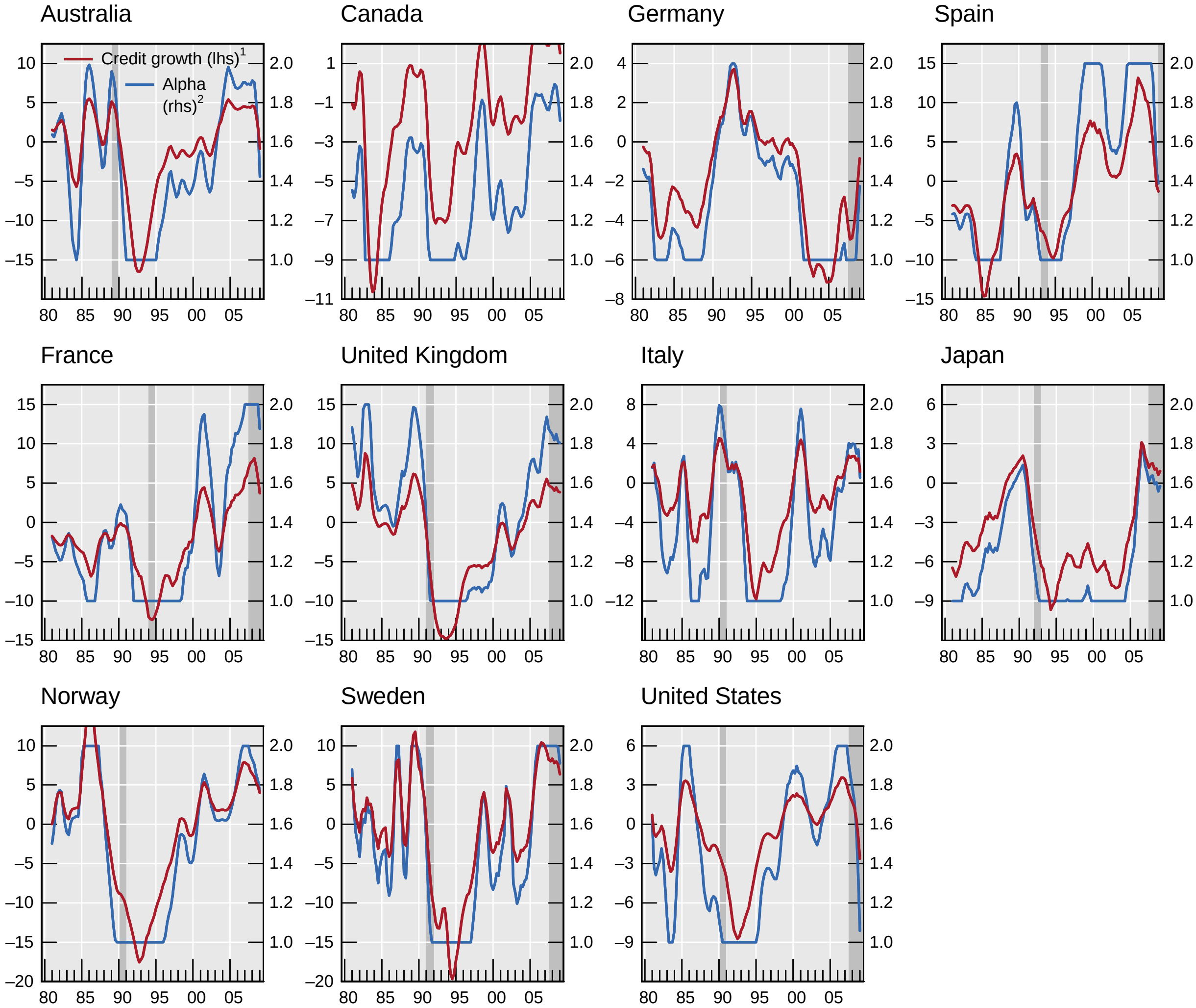
The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

[1] Four-quarter average real growth minus its 15-year rolling average, in percentage points. [2] The adjustment factor alpha is based on a linear formula. Alpha equals 1 if real GDP growth is more than one standard deviation (std) below its 15-year rolling average. The maximum adjustment is 2. The slope of the linear formula is 1 / (2*std).

Sources: National data; BIS calculations.

Graph A4.2

Credit growth



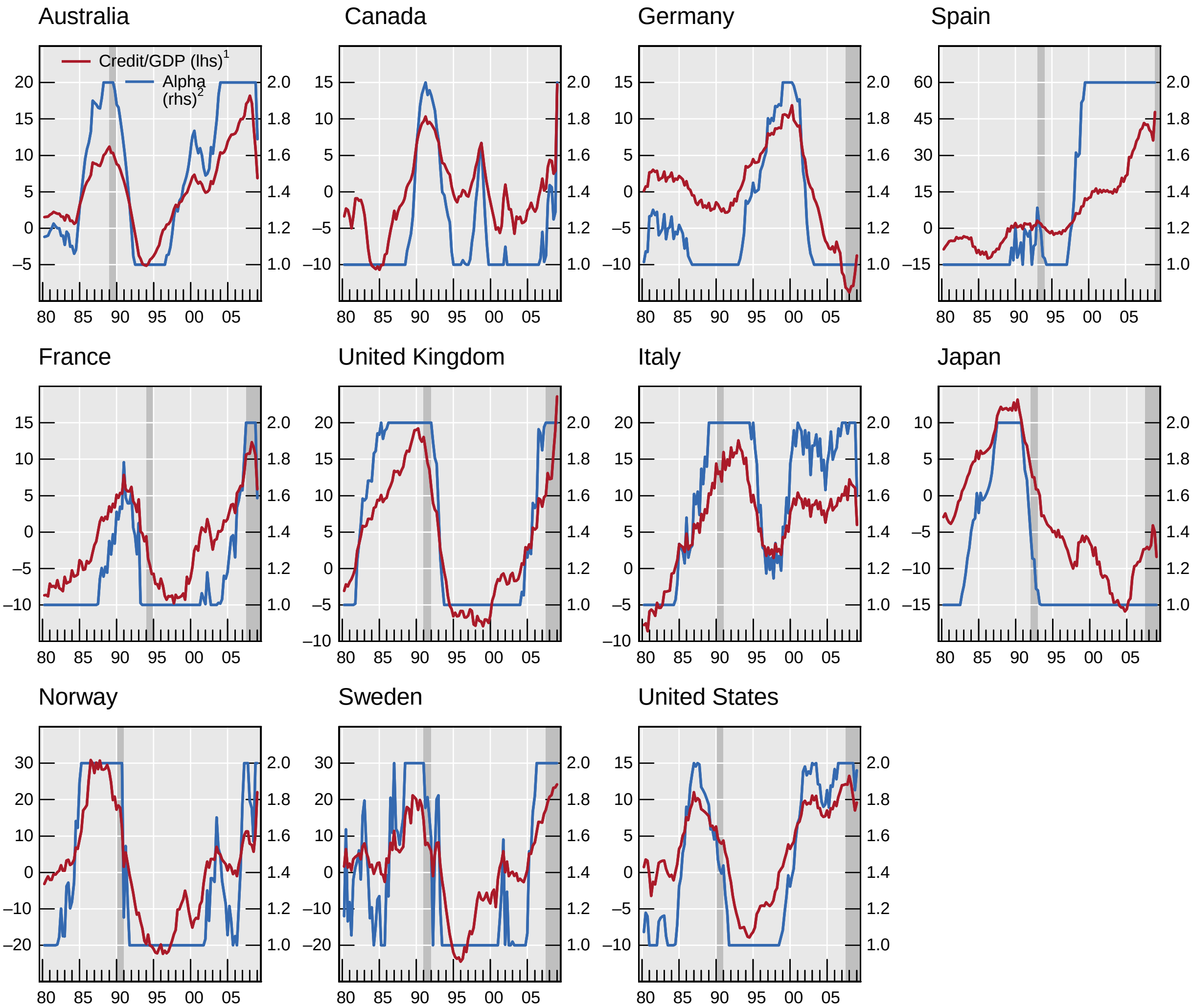
The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

[1] Four-quarter average real growth minus its 15-year rolling average, in percentage points. [2] The adjustment factor alpha is based on a linear formula. Alpha equals 1 if real credit growth is more than one standard deviation (std) below its 15-year rolling average. The maximum adjustment is 2. The slope of the linear formula is 1 / (2*std).

Sources: National data; BIS calculations.

Graph A4.3

Credit/GDP



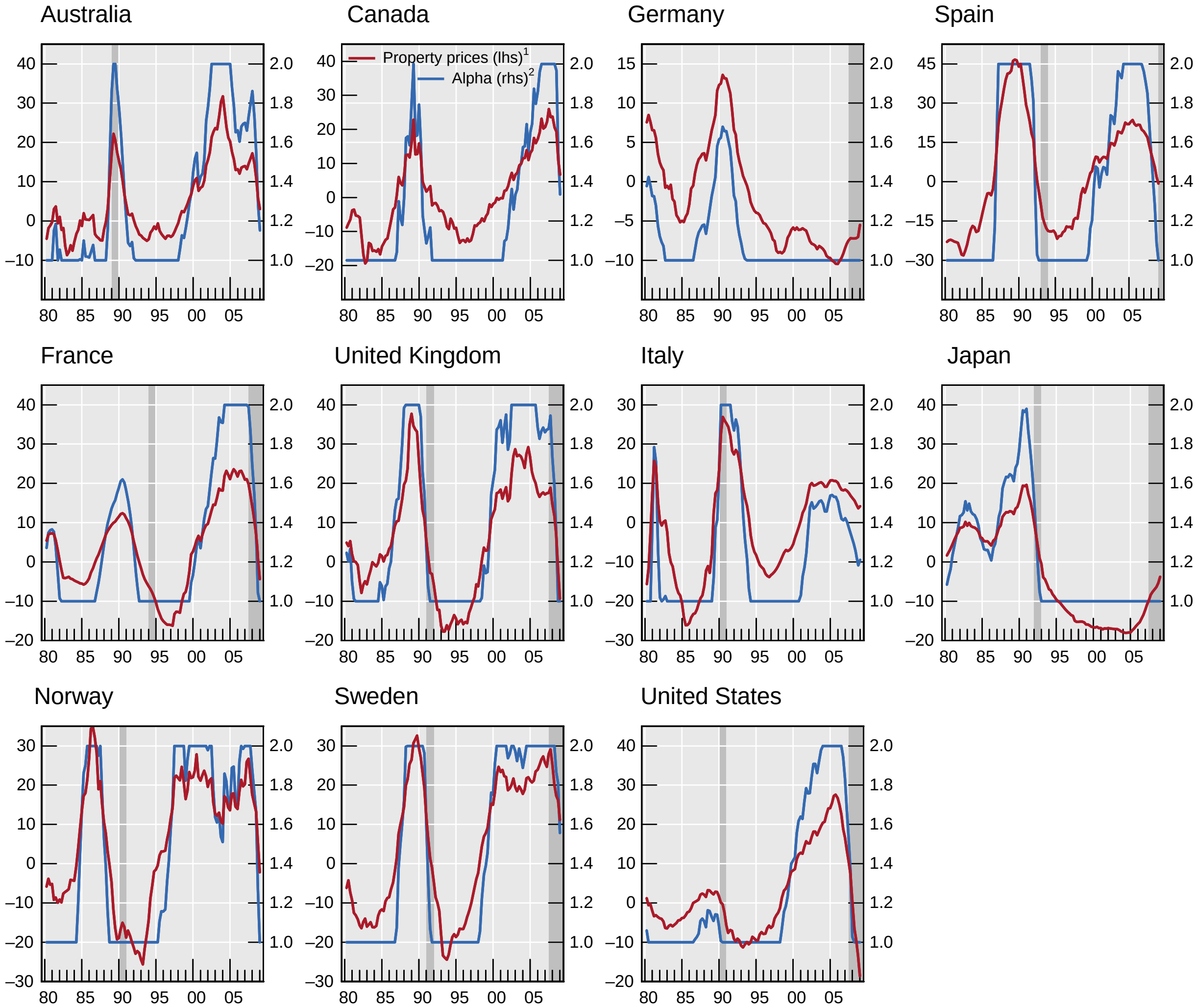
The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

[1] Deviation from the one-sided long-term trend (that is, a trend determined only from information available at the time assessments are made) using a very high value of the smoothing parameter; in percentage points. [2] The adjustment factor alpha is based on a linear formula. Alpha equals 1 if the credit/GDP gap is below 0. The maximum adjustment is 2. The slope of the linear formula is 1/10.

Sources: National data; BIS calculations.

Graph A4.4

Property prices



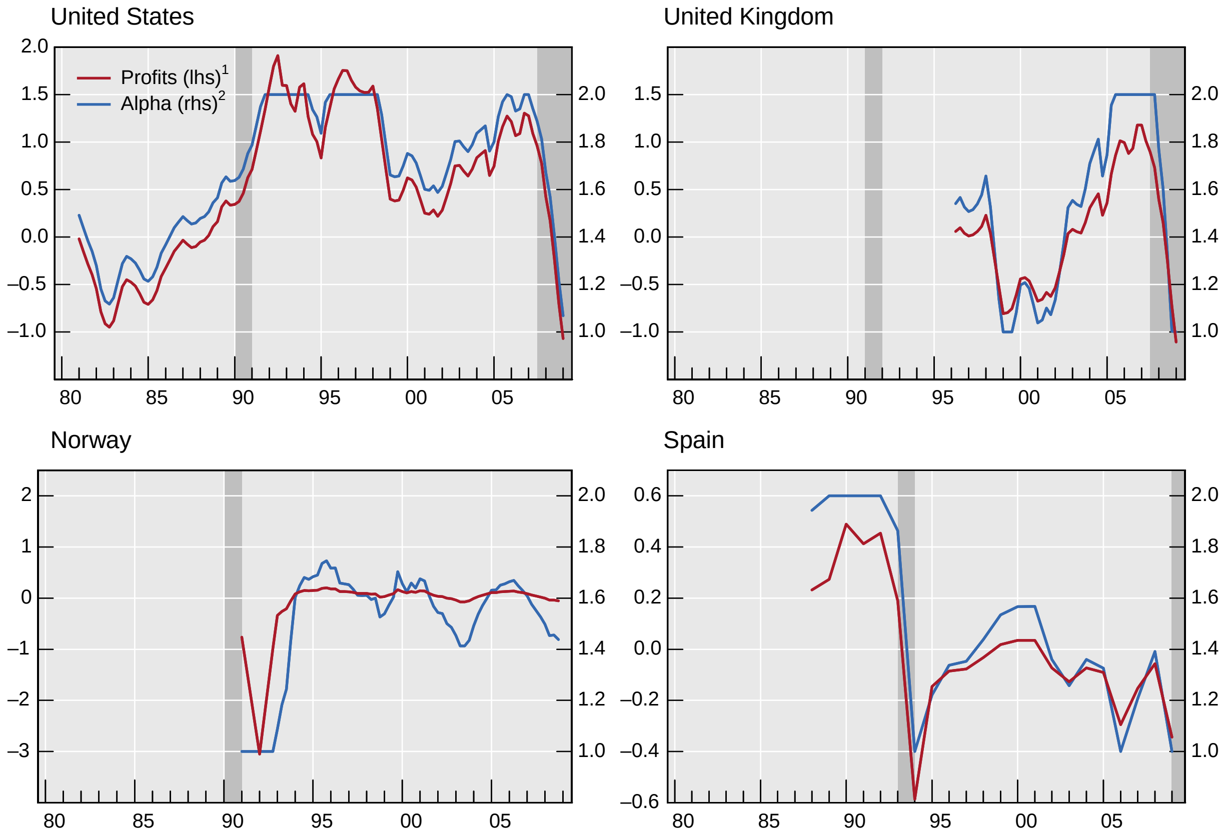
The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

[1] Deviation from the one-sided long-term trend (that is, a trend determined only from information available at the time assessments are made) using a very high value of the smoothing parameter; in per cent. [2] The adjustment factor alpha is based on a linear formula. Alpha equals 1 if the property price gap is below 0. The maximum adjustment is 2. The slope of the linear formula is 1/20.

Sources: National data; BIS calculations.

Graph A4.5

Profits



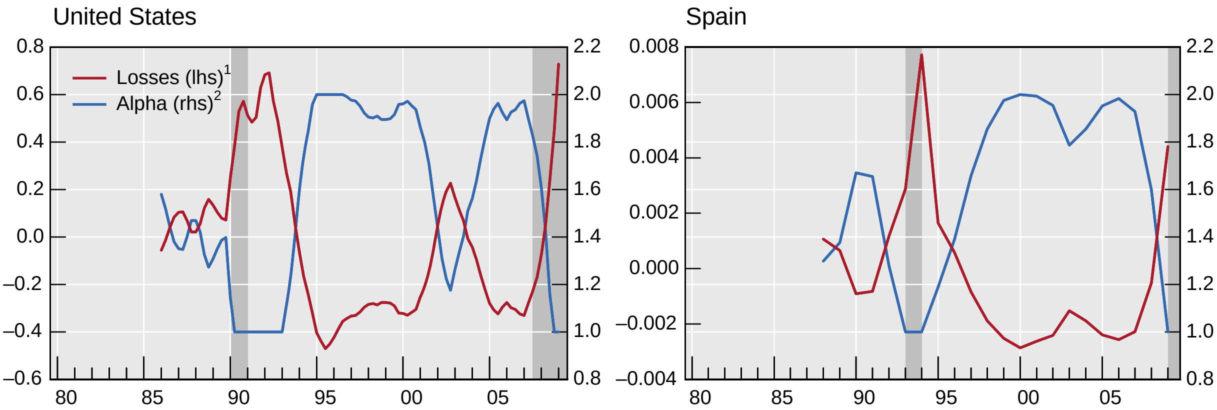
The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

[1] Pre-tax profits as a percentage of total assets. Four-quarter average minus its 15-year rolling average, in percentage points. [2] The adjustment factor alpha is based on a linear formula. Alpha equals 1 if the profits are more than one standard deviation (std) below their 15-year rolling average. The maximum adjustment is 2. The slope of the linear formula is 1 / (2*std).

Sources: National data; BIS calculations.

Graph A4.6

Proxies for gross losses



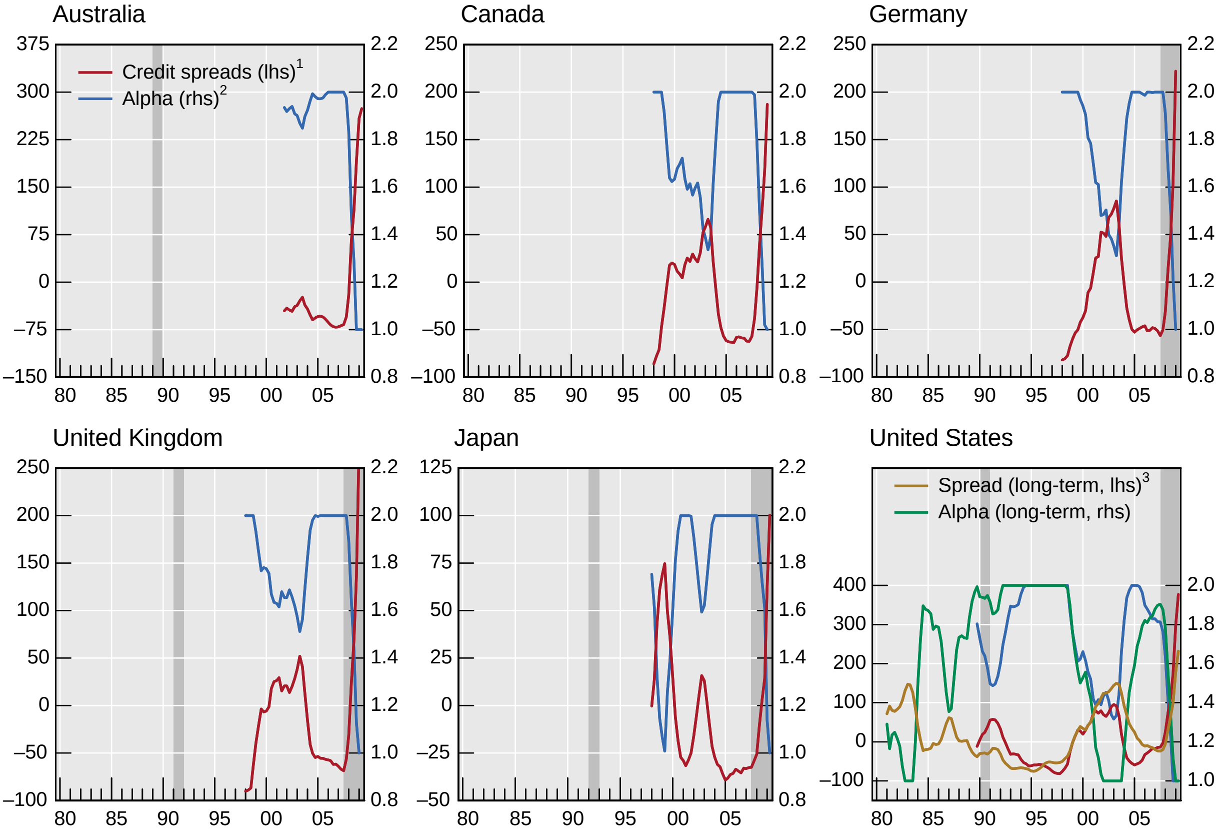
The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

[1] For Spain: flow of specific provisions as a percentage of total asset; for the United States: charge-off rates. Four-quarter average real growth minus its 15-year rolling average, in percentage points. [2] The adjustment factor alpha is based on a linear formula. Alpha equals 1 if bank losses are more than 1.5 standard deviations (std) above their 15-year rolling average. The maximum adjustment is 2. The slope of the linear formula is 1 / (2*std).

Sources: National data; BIS calculations.

Graph A4.7

Credit spreads



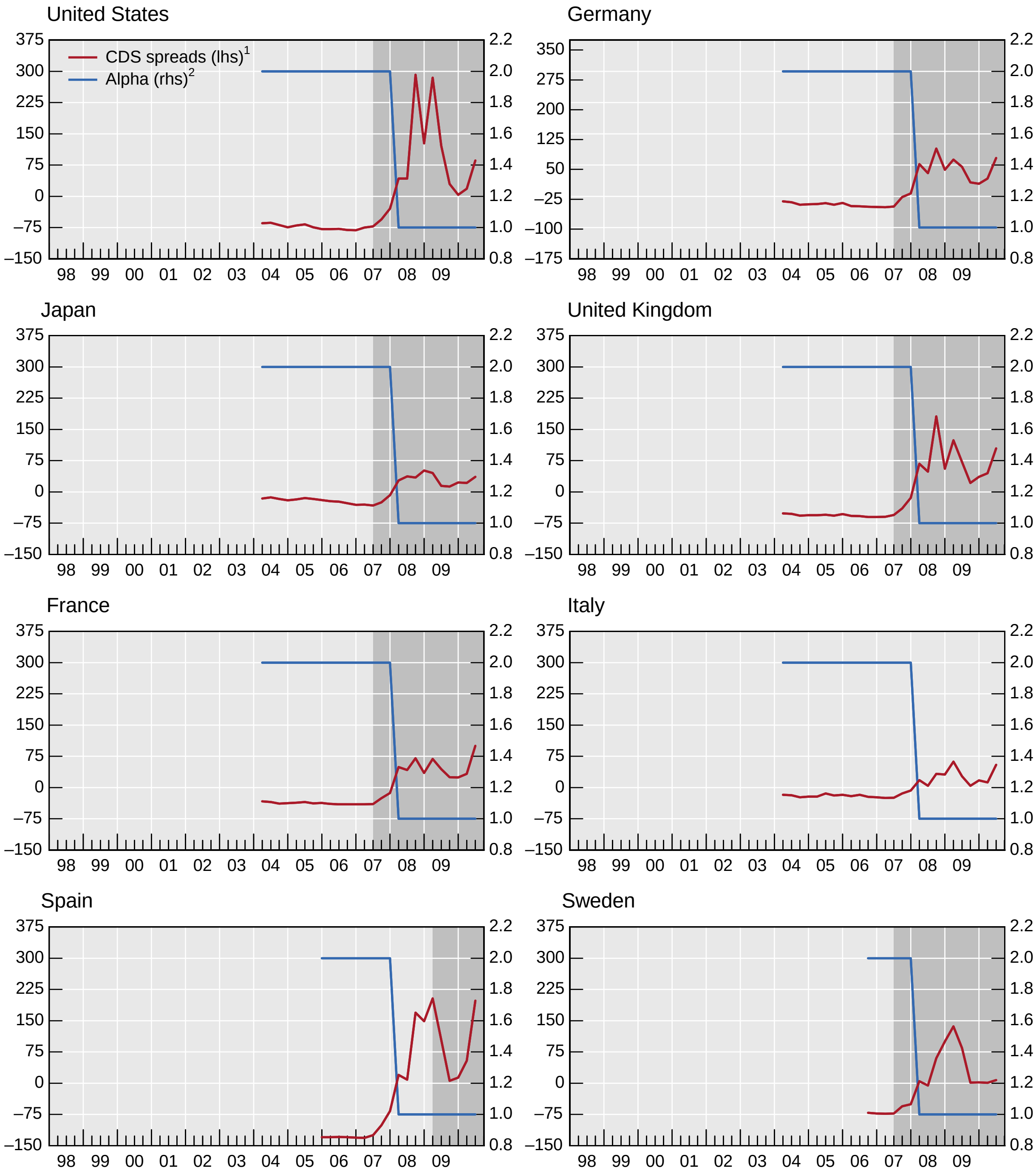
The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

[1] BBB medium-term (7-10 years) corporate bond spreads (Merrill Lynch); four-quarter rolling average minus its 15-year rolling average, in basis points. [2] The adjustment factor alpha is based on a linear formula. Alpha equals 1 if bank credit spreads are more than 1.5 standard deviations (std) above their 15-year rolling average. The maximum adjustment is 2. The slope of the linear formula is 1 / (2*std). [3] Baa long-term (20-30 years) corporate bond spreads (Moody's); four-quarter rolling average minus its 15-year rolling average, in basis points.

Sources: Merrill Lynch; Moody's; national data; BIS calculations.

Graph A4.8

CDS spreads



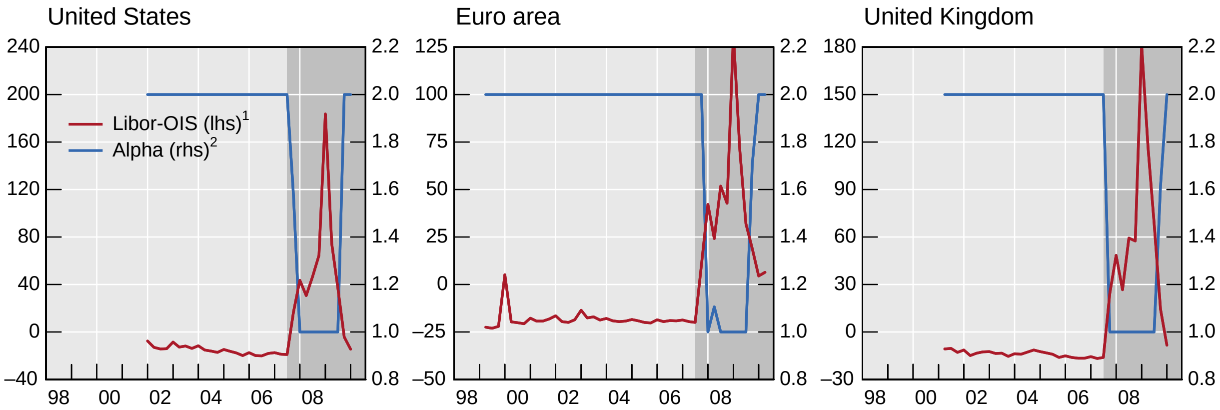
The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

[1] CDS index for banks minus its 15-year rolling average, in basis points. [2] The adjustment factor alpha is based on a linear formula. Alpha equals 1 if bank CDS spreads are more than 1.5 standard deviations (std) above their 15-year rolling average. The maximum adjustment is 2. The slope of the linear formula is 1 / (2*std).

Sources: Markit; BIS calculations.

Graph A4.9

Libor-OIS spreads



The vertical shaded areas indicate initial years of system-wide banking distress or severe strains in the banking system resulting in negative effects to the macroeconomy.

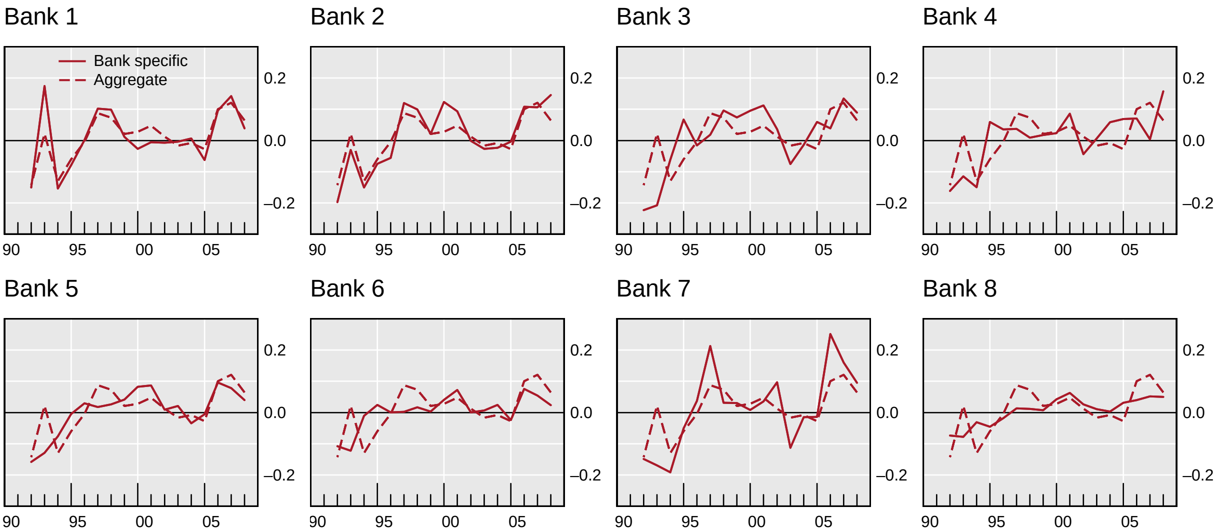
[1] Three-month interbank rates minus three-month overnight index swaps, in basis points. [2] The adjustment factor alpha is based on a linear formula. Alpha equals 1 if bank Libor-OIS spreads are more than 1.5 standard deviations (std) above their 15-year rolling average. The maximum adjustment is 2. The slope of the linear formula is 1 / (2*std)

Sources: Bloomberg; BIS calculations.

Annex 5: Bank-specific conditioning variables and the corresponding alphas

Graph A5.1

Asset growth, Norway: bank-specific versus aggregate[1]

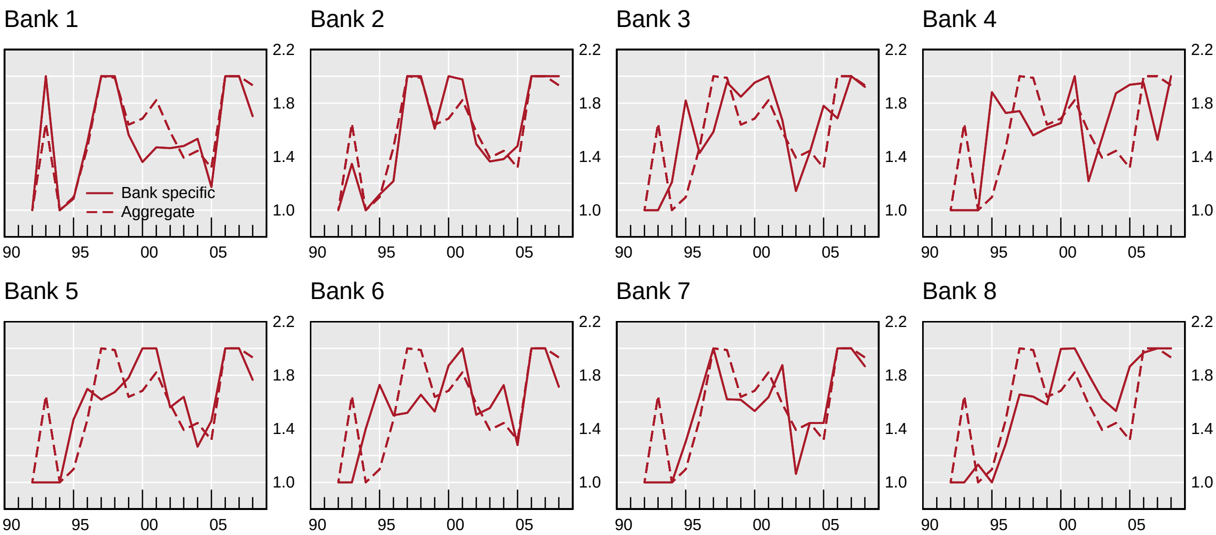


[1] Deviation from bank-specific 15-year rolling average, for aggregate series its 15-year rolling average is used. Data are based on consolidated bank balance sheets. The aggregate is the sum of the banks shown.

Sources: National data; BIS calculation.

Graph A5.2

Asset growth, Norway: bank-specific versus aggregate: alphas[1]

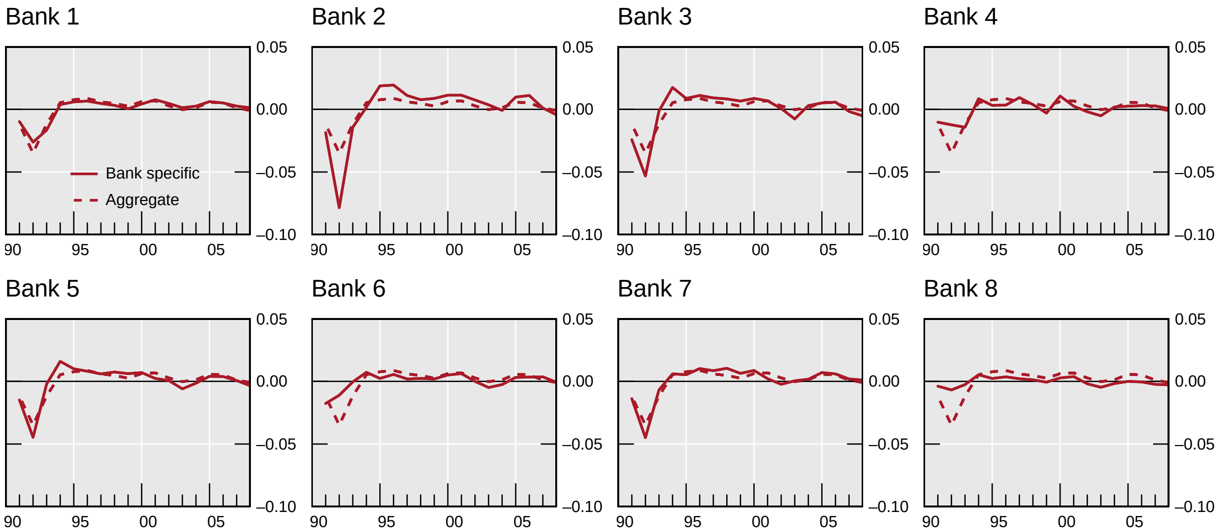


[1] The adjustment factor alpha is based on a linear formula. Alpha equals 1 if the bank-specific asset growth is more than one (bank-specific) standard deviation (std) below its 15-year rolling average. The maximum adjustment is 2. The slope of the linear formula is 1/(2*std). Alpha for the aggregate asset growth is based on the rolling average and standard deviation of the aggregate series.

Sources: National data; BIS calculation.

Graph A5.3

Pre-tax profits/assets, Norway: bank-specific versus aggregate[1]

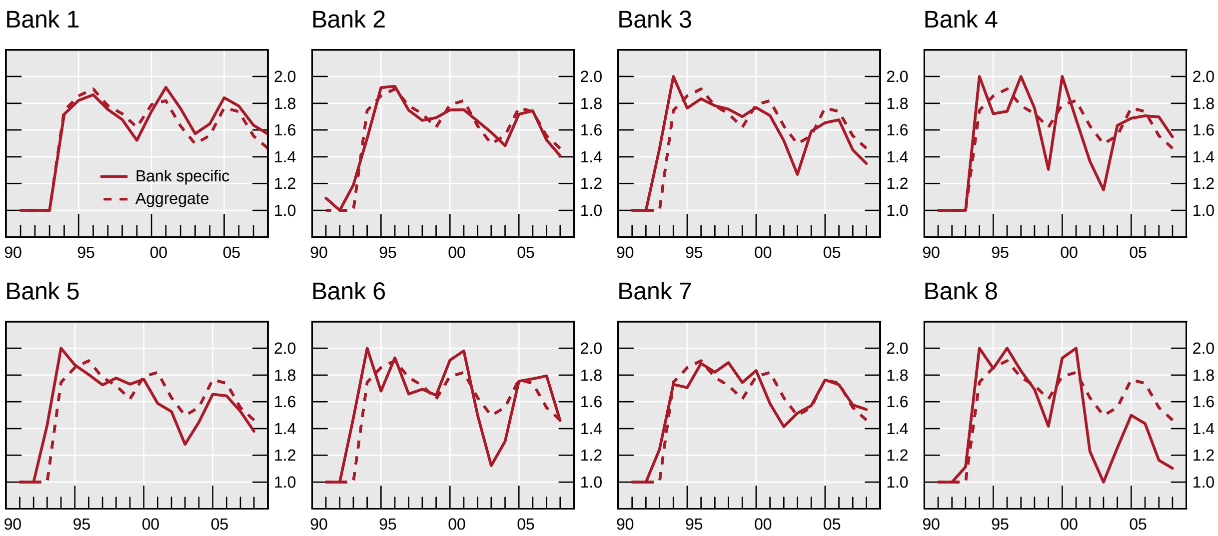


[1] Deviation from bank-specific 15-year rolling average, for aggregate series its 15-year rolling average is used. Data are based on consolidated bank balance sheets. The aggregate is the sum of the banks shown.

Sources: National data; BIS calculation.

Graph A5.4

Pre-tax profits/assets, Norway: bank-specific versus aggregate: alphas[1]

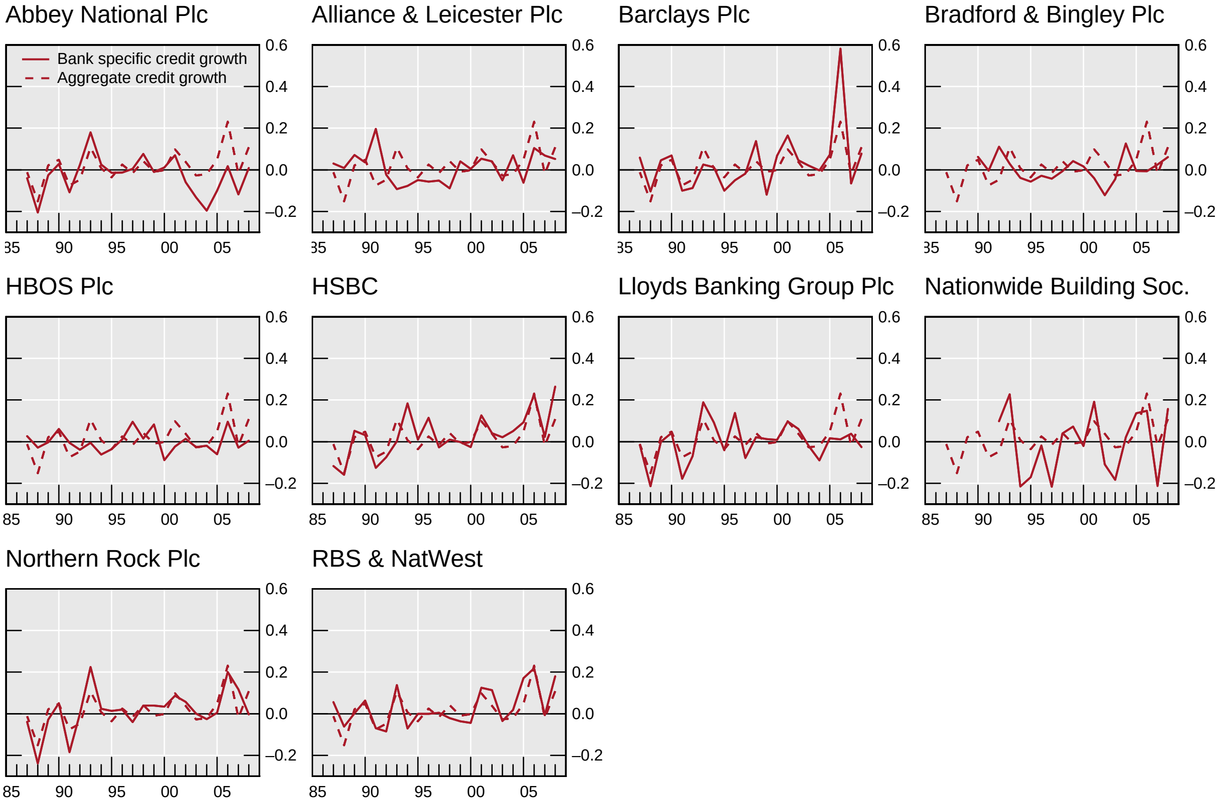


[1] The adjustment factor alpha is based on a linear formula. Alpha equals 1 if the bank-specific asset growth is more than one (bank-specific) standard deviation (std) below its 15-year rolling average. The maximum adjustment is 2. The slope of the linear formula is 1/(2*std). Alpha for the aggregate asset growth is based on the rolling average and standard deviation of the aggregate series.

Sources: National data; BIS calculation.

Graph A5.5

Asset growth, UK: bank-specific versus aggregate[1]

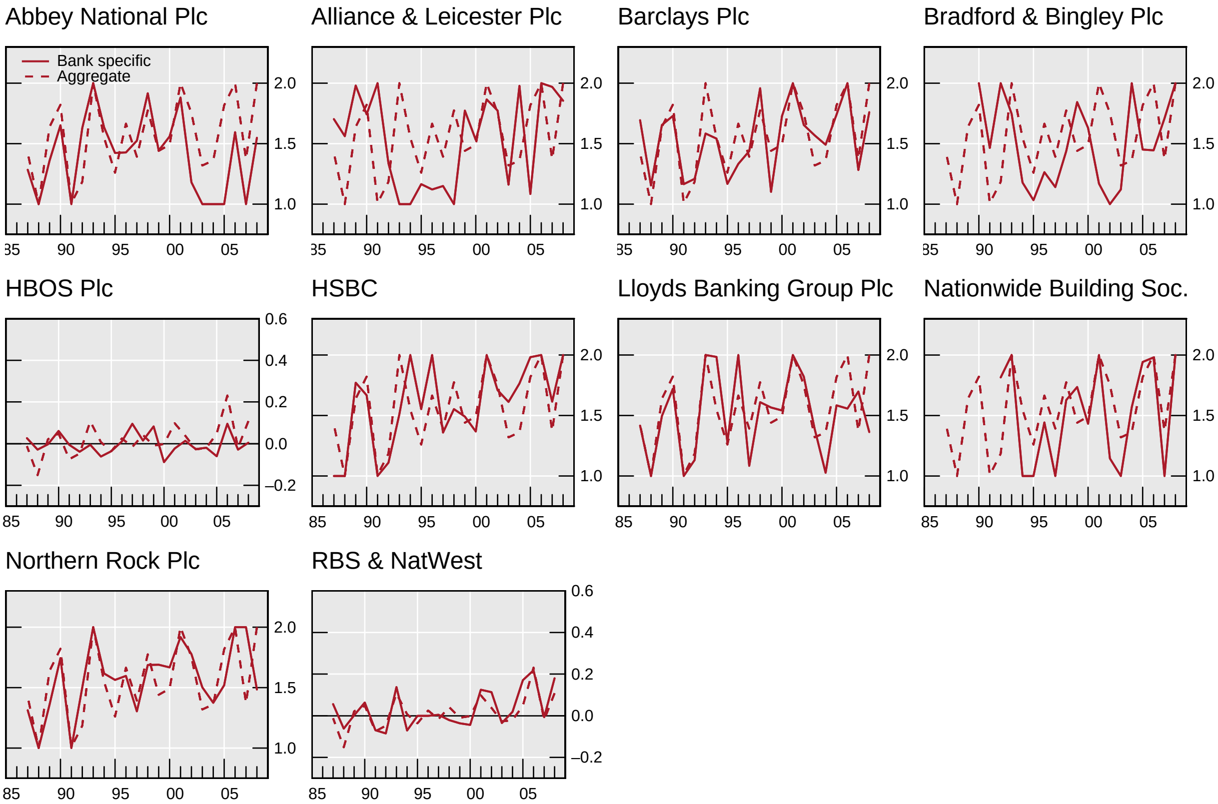


[1] Deviation from bank-specific 15-year rolling average, for aggregate series its 15-year rolling average is used. Data are based on consolidated bank balance sheets. The aggregate is the sum of the banks shown.

Sources: National data; BIS calculation.

Graph A5.6

Asset growth, UK: bank-specific versus aggregate: alphas[1]

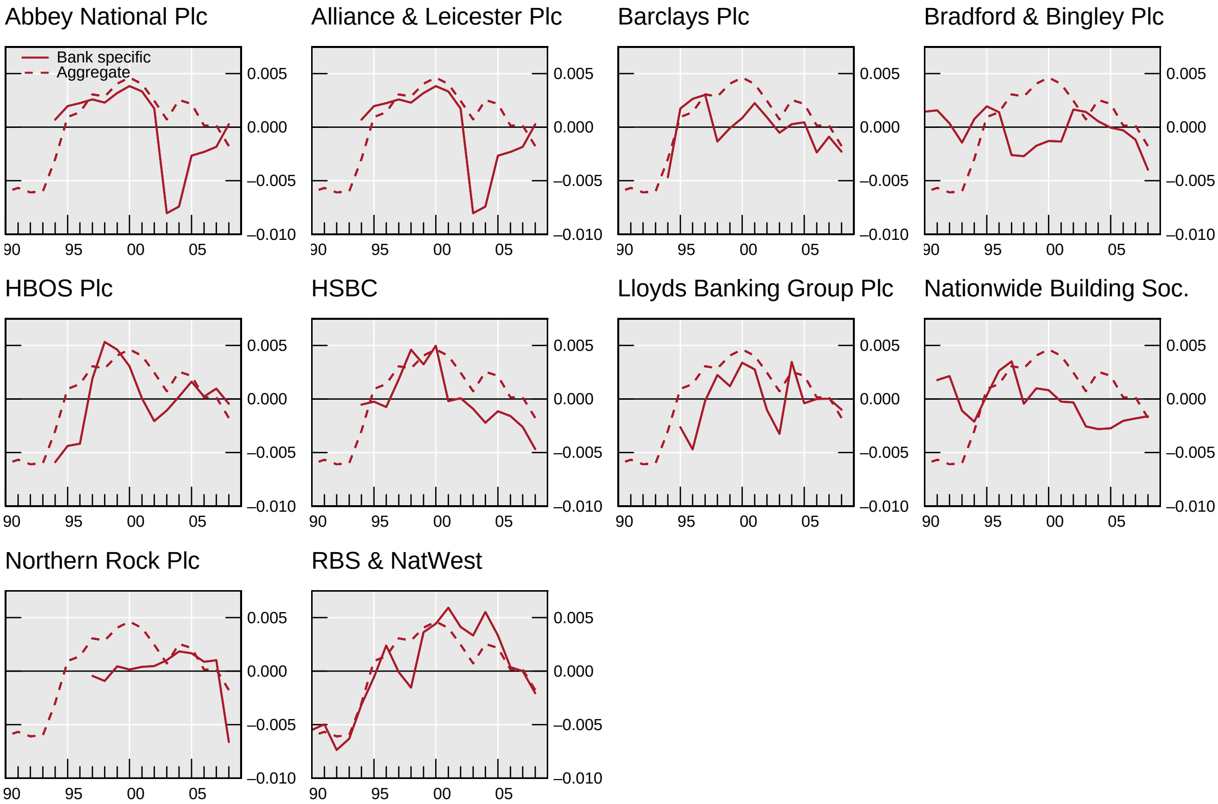


[1] The adjustment factor alpha is based on a linear formula. Alpha equals 1 if the bank-specific asset growth is more than one (bank-specific) standard deviation (std) below its 15-year rolling average. The maximum adjustment is 2. The slope of the linear formula is 1/(2*std). Alpha for the aggregate asset growth is based on the rolling average and standard deviation of the aggregate series.

Sources: Bankscope; BIS calculation.

Graph A5.7

Pre-tax profits/assets, UK: bank-specific versus aggregate[1]

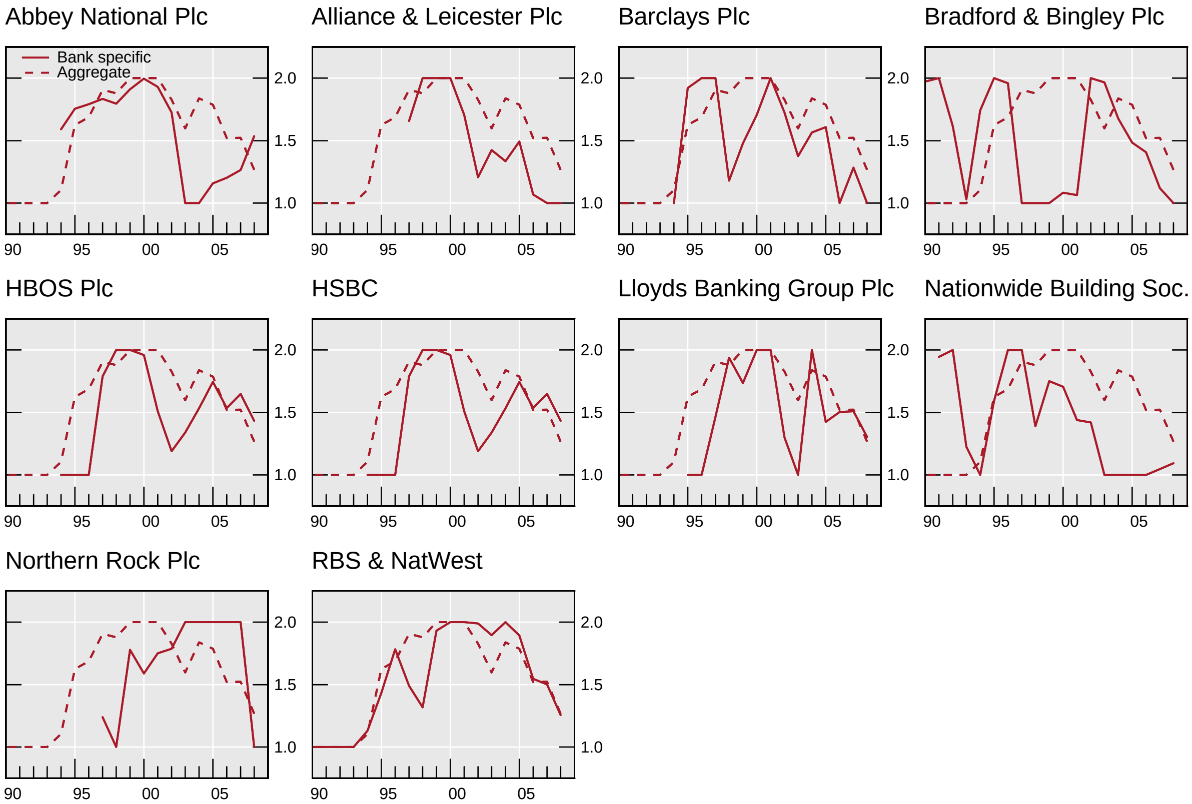


[1] Deviation from bank-specific 15-year rolling average, for aggregate series its 15-year rolling average is used. Data are based on consolidated bank balance sheets. The aggregate is the sum of the banks shown.

Sources: Bankscope; BIS calculation.

Graph A5.8

Pre-tax profits/assets, UK: bank-specific versus aggregate, alphas[1]

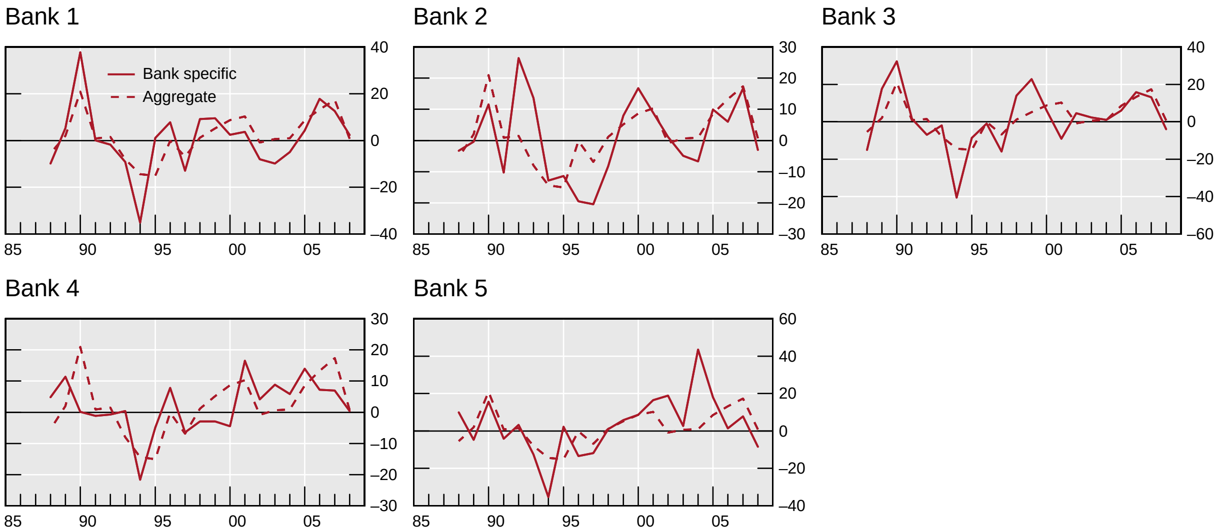


[1] Pre-tax profits as a percentage of total assets. The adjustment factor alpha is based on a linear formula. Alpha equals 1 if the bank-specific pre-tax profits over assets are more than one (bank-specific) standard deviation (std) below their 15-year rolling average. The maximum adjustment is 2. The slope of the linear formula is 1/(2*std). Alpha for the aggregate pre-tax profit to asset ratio is based on the rolling average and standard deviation of the aggregate series.

Sources: Bankscope; BIS calculation.

Graph A5.9

Asset growth, Spain: bank-specific versus aggregate[1]

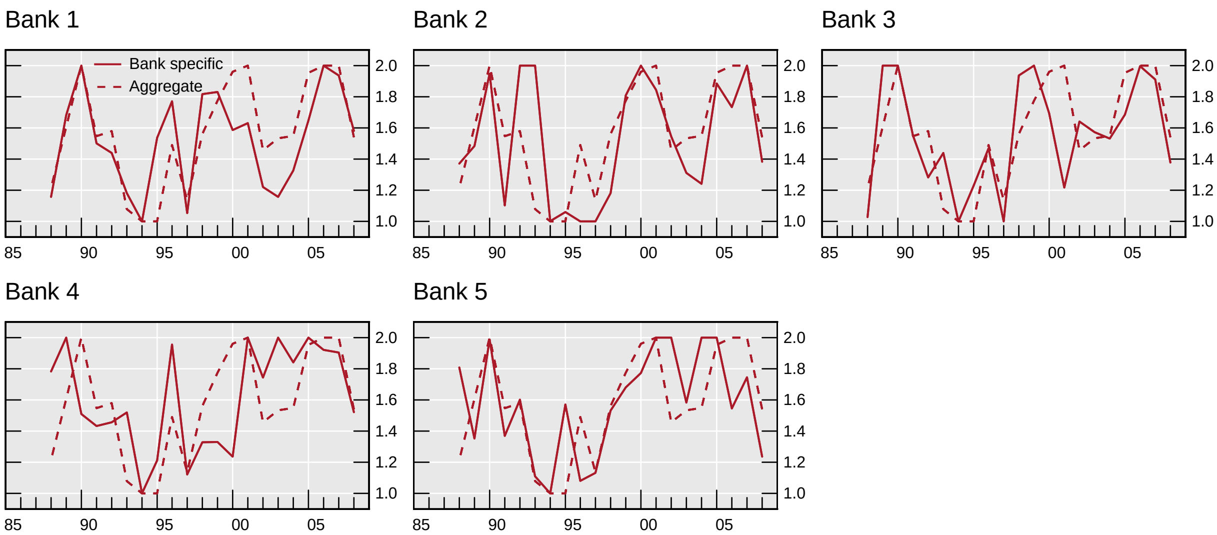


[1] Deviation from bank-specific 15-year rolling average, for aggregate series its 15-year rolling average is used. Data are based on consolidated bank balance sheets. The aggregate is the sum of the banks shown.

Sources: National data; BIS calculation.

Graph A5.10

Asset growth, Spain: bank-specific versus aggregate: alphas[1]



[1] The adjustment factor alpha is based on a linear formula. Alpha equals 1 if the bank-specific asset growth is more than one (bank-specific) standard deviation (std) below its 15-year rolling average. The maximum adjustment is 2. The slope of the linear formula is 1/(2*std). Alpha for the aggregate asset growth is based on the rolling average and standard deviation of the aggregate series

Sources: National data; BIS calculation.

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