

The credit-to-GDP gap and complementary indicators for macroprudential policy: Evidence from the UK¹

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Abstract: The financial crisis has demonstrated the need for a set of macroprudential policy tools that can be used to mitigate systemic risk. Focusing on the UK, our paper reviews the performance of the Basel III credit-to-GDP gap which, alongside judgement, is to be used as a reference guide in setting the countercyclical capital buffer. We find that this measure worked well in providing an advance signal of past UK episodes of banking system distress. But this does not guarantee future signalling success. We therefore evaluate some conceptual shortcomings of the credit gap and suggest complementary indicators.

Key words: Credit-to-GDP gap, countercyclical capital buffer, early warning indicators, financial crises, macroprudential policy

1 Introduction

The financial crisis has demonstrated the need for a broader set of policy tools that can be used to mitigate systemic risk. Time-varying macroprudential policy aims to enhance the resilience of the banking system and over-exuberance in the supply of credit by discouraging the build-up of financial imbalances that might otherwise have led to a systemic banking crisis (Bank of England (2009), CGFS (2010), Bank of England (2011b), Borio (2011), FSB/IMF/BIS (2011) and IMF (2011) among others). The Basel III framework has proposed the countercyclical capital buffer as one tool that would be applied at the aggregate level of national banking systems. The countercyclical capital buffer is an extension to the regulatory capital framework for banks which policymakers will be able to adjust in a time-varying way. Other time-varying macroprudential tools, including sectoral capital requirements, leverage ratios and liquidity requirements, will also likely be important.

To help guide the activation and release of the countercyclical capital buffer, the Basel Committee on Banking Supervision has suggested that it should be raised when a country's credit-to-GDP ratio exceeds its long-run trend by two percentage points.⁸ This BCBS guide will serve as a common international guideline for policymakers taking buffer decisions, alongside other indicators and judgement.

¹ The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or the Financial Policy Committee. We are grateful to Timothy Richards for research assistance. We also thank participants and discussant Vladimir Borgey at the Conference on Macroeconomic and Financial Vulnerability Indicators in Advanced Economies in Strasbourg in September 2012, seminar participants at the Bank of England, an anonymous referee, David Aikman, Oliver Burrows, Jas Ellis, Hanno Stremmel and Victoria Saporta for helpful comments.

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⁸ See BCBS (2010).

This paper considers the credit-to-GDP gap and other indicators which may help to guide the setting of macroprudential capital requirements at both an aggregate and sectoral level in a UK context; indicators for other potential areas of macroprudential policy, such as liquidity requirements or structural policies, are left for future work. The Financial Policy Committee of the Bank of England has published lists of core indicators for the countercyclical capital buffer and sectoral capital requirements (Bank of England (2013)). Our analysis should be viewed as complementary: we discuss a subset of the indicators in Bank of England (2013) in more detail with a focus on indicators for which we have long time series available. We take the credit-to-GDP gap as a starting point, arguing that the gap as defined by the BCBS worked well in providing an advance signal of past UK crises. This is despite us using a real-time measure (see Edge and Meisenzahl (2011) for a contrasting discussion of this issue).

But, as noted in Bank of England (2013), no single indicator can ever provide a perfect guide to systemic risks or the appropriate policy responses, given the complexity of financial interlinkages, the tendency for the financial system to evolve over time and time lags before risks become apparent. Policymakers will also need to monitor a wide and time-varying set of indicators, depending on the emerging risks. In this paper, we therefore discuss additional indicators that might complement the credit-to-GDP gap, both in the context of having been useful in past crises in the UK and elsewhere and in helping to address some of the credit-to-GDP gap's conceptual shortcomings. In particular, we argue that the sources and quality of credit are important, suggesting the need not only for an aggregate capital tool such as the countercyclical capital buffer but also sectoral tools such as sectoral capital requirements. Finally, we discuss indicators that might help determine when to release the capital buffers.

In discussing other indicators, we take guidance from the literature based on cross-country analyses (for example, Kaminsky and Reinhart (1999), Drehmann *et al.* (2010), Drehmann *et al.* (2011), Borio and Lowe (2002, 2004) and Barrell *et al.* (2010)). Cross-country studies have the obvious advantage of relying on more observations which gives more rigour to understanding the indicators that have tended to signal banking crises in the past. However, they also have drawbacks. For example, there may be little gained by including countries with different institutional arrangements and financial structures in the same panel analysis. Moreover, data definitions may not be homogeneous across countries and time series employed in panel approaches tend to be limited. By taking the lessons from the cross-country literature but focusing on the UK only for our own analysis, we have the advantage of being less limited by data availability, can focus more closely on individual series and are able to provide greater context. But the number of crises is small compared with cross-country studies: the UK experienced three episodes of banking system distress over the past 50 years. Our dataset begins in the late 1960s for most series, covering the secondary banking crisis from Q4 1973 to Q4 1975, the small banks' crisis from Q3 1990 to Q2 1994 and the current crisis from Q3 2007 onwards.⁹ Some common elements were evident in all three episodes: rapid credit expansions fuelled property price booms and financial institutions encountered liquidity problems as funding markets dried up.

⁹For the secondary banking crisis see Reid (1982) and for the small banks' crisis Logan (2000).

The secondary banking crisis was the result of so-called unregulated ‘fringe’ institutions funding themselves in money markets and investing these into, largely, commercial property developments. Tightening monetary policy in 1973 contributed to the drying up of short-term funding in money markets and the emergence of the problems at fringe institutions. To stop problems passing into the regulated banking system, a ‘lifeboat’ was set up whereby regulated banks were given responsibility for supporting ailing fringe institutions, in cooperation with the Bank of England. The small banks’ crisis was not dissimilar. Again, asset prices, particularly in commercial and residential real estate, rose, alongside credit. As monetary policy was tightened, property markets turned and smaller banks, faced with losses, lost access to money markets. From mid-1991, the Bank of England provided liquidity support to a few small banks as their failure might have caused further disruption in funding markets. Rapid commercial and residential property price growth was also a feature ahead of the current crisis. This was accompanied by a surge in lending within the financial system as, for example, mortgages were securitised and sold on, increasing interconnectedness between institutions. And banks’ funding once again proved a weak point. As global wholesale funding markets dried up in 2007-8, banks experienced liquidity problems that soon turned into solvency problems. But this time, problems were not limited to small banks – two of the UK’s largest banks, LBG and RBS, had to seek government support.

2 The credit-to-GDP gap for the UK

Minsky (1972) and Kindleberger (1978) both argue that credit booms tend to sow the seeds of crises. In terms of empirical underpinning, several studies, including Alessi and Detken (2009), Borgy *et al.* (2009), Borio and Lowe (2002, 2004), Drehmann *et al.* (2010), Drehmann *et al.* (2011) and Schularick and Taylor (2012), have found that indicators of excess credit growth are powerful in providing advance signals of financial crises. Dell’Ariccia *et al.* (2012) find that a third of credit booms are followed by crises and three fifths are followed by a period of economic underperformance (measured by the difference between GDP growth relative to its long-run trend) in the six years following the end of the boom. And micro evidence in Mendoza and Terrones (2008) suggests that bank capital adequacy standards tend to fall during credit booms (at least in EMEs).

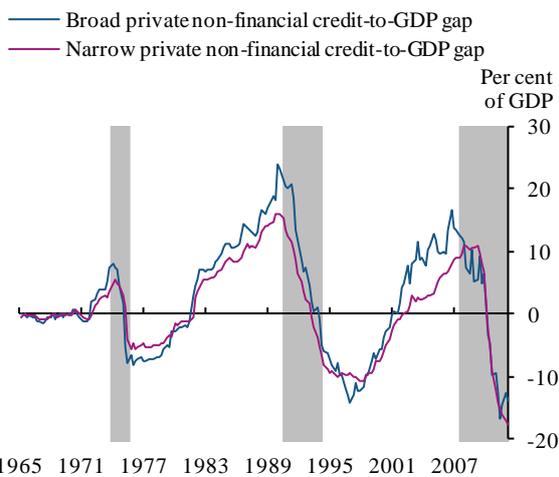
But defining a credit boom is tricky. The BCBS has suggested deviations of a credit-to-GDP ratio from its long-term trend for this purpose. The credit measure it recommends is broad credit to the household and private non-financial corporate (PNFC) sector, including non-banks and lending from abroad. The BCBS further proposes that the long-run trend be calculated by a one-sided, or ‘real-time’, Hodrick-Prescott (HP) filter with a smoothing parameter of 400,000.¹⁰

Chart 1 illustrates this measure for the UK, showing that the broad measure would have signalled the need to tighten the countercyclical capital buffer ahead of the past three

¹⁰ An HP filter is used to separate slow-moving trends from cycles in the data. The trend is calculated by minimising a function containing the deviation of the trend from the data and the variation in the growth rate of the trend. A smoothing parameter (the lambda) determines the weight put on the proximity of the trend to the data and the variation in the trend.

episodes of banking system distress in the UK. Although the data needed to calculate the broad measure are only available since 1987 in the UK, we have constructed an approximation of the credit gap back to the 1960s by extrapolating the credit series using data on narrow credit (UK-resident bank lending to resident households and PNFCs) that go back to 1963. We also show the narrow series given that the data included in the broad series on lending to PNFCs is based on approximations and the narrower data are of higher quality for the UK. Both series do well, although the narrow series would have suggested a more gradual tightening of the buffer ahead of the current crisis.

Chart 1: Gap of broad and narrow HH and PNFC credit-to-GDP relative to long-term trend^{(a)(b)(c)}



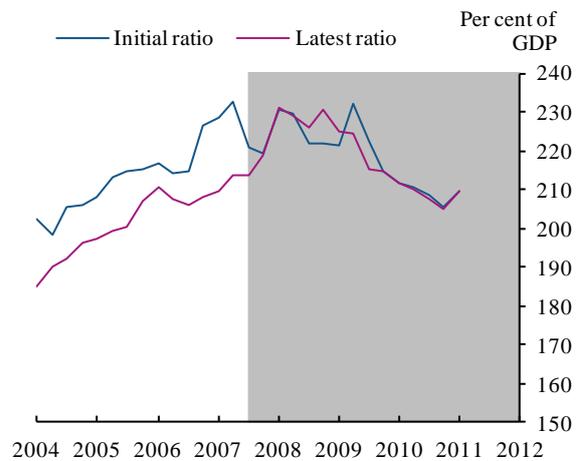
Source: ONS, Bank of England and Bank calculations.

(a) The credit-to-GDP gap is calculated as the percentage point difference between the credit to GDP ratio and its long-term trend, where the trend is based on a one-sided/two-sided HP filter with a smoothing parameter of 400,000.

(b) Broad credit is defined here as debt claims on the UK private non-financial sector. This includes all liabilities of the household and not-for-profit sector and private non-financial corporations' loans and debt securities excluding derivatives, direct investment loans and loans secured on dwellings. ONS data are not available before 1990. Before then, stable relationships between the ONS household and private non-financial corporation debt data and Bank of England household and private non-financial corporation lending data are assumed and the ONS household and private non-financial corporation debt series is assumed to grow at the same rate as the Bank of England household and private non-financial corporation lending series.

(c) Narrow credit comprises UK-resident monetary financial institution s' sterling and foreign currency lending to households and PNFCs.

Chart 2: Initial and revised estimates of the credit-to-GDP ratio^(a)



Source: ONS, Bank of England and Bank calculations.

(a) Credit is defined here as debt claims on the UK private non-financial sector. This includes all liabilities of the household sector and private non-financial corporations' loans and debt securities.

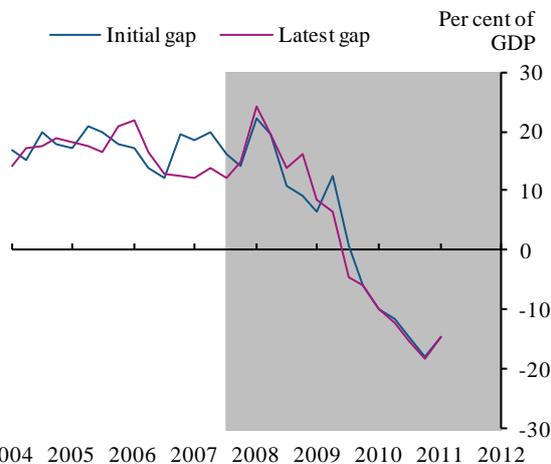
Next, we discuss three empirical challenges raised in relation to the credit-to-GDP gap and how these relate to the usefulness of the credit-to-GDP gap in assessing risk to the UK financial system.

Challenge i): The role of data revisions

Building on work by Orphanides and van Norden (2002), Edge and Meisenzahl (2011) question the reliability of the credit-to-GDP gap in real time. They argue that revisions to the underlying data used to calculate the credit-to-GDP ratio may lead to significant policy error,

though they conclude that such revisions are not large in the case of the US and are therefore unlikely to lead to mistakes. But this may be a more significant problem in the UK. To check this, we analyse real-time data on GDP and broad credit to households and PNFCs. Our dataset includes (most) vintages from December 2004 onwards. As Chart 2 shows, revisions over this period were significant for the credit-to-GDP ratio. But it does not follow from this that revisions would have been a major source of policy error. Chart 3 shows the credit-to-GDP gap using data available in real time and the latest data, suggesting that revisions over this period were smaller for the gap, i.e. ratio relative to trend, than for the ratio itself. This stems from the fact that revisions are autocorrelated, so they pull the trend up and down as well as the ratio, reducing the effect of revisions on the gap estimate.

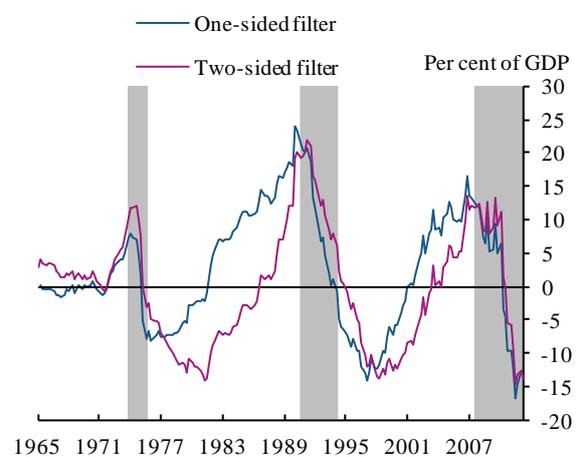
Chart 3: Initial and revised estimates of the credit-to-GDP gap^{(a)(b)}



Source: ONS, Bank of England and Bank calculations.

(a) The credit-to-GDP gap is calculated as in footnote (a) in Chart 1.
 (b) Credit is defined here as debt claims on the UK private non-financial sector. This includes all liabilities of the household sector and private non-financial corporations' loans and debt securities.

Chart 4: Credit-to-GDP gaps calculated with one- and two-sided HP filter^{(a)(b)}



Source: ONS, Bank of England and Bank calculations.

(a) The credit-to-GDP gap is calculated as the percentage point difference between the credit to GDP ratio and its long-term trend, where the trend is based on a one-sided/two-sided HP filter with a smoothing parameter of 400,000.
 (b) Please see Chart 1 footnote (b) for the definition of credit.

Challenge ii): The choice of trend

Edge and Meisenzahl (2011) also argue that the 'true' underlying trend, measured using a two-sided HP filter, may differ substantially from real-time estimates of the trend, measured using a one-sided filter. The one-sided filter uses only data available up to each observation, whereas the two-sided filter calculates the trend over the whole sample.¹¹ They find that this makes a substantial difference to estimates of the gap in the US and warn that this may lead to policy errors.

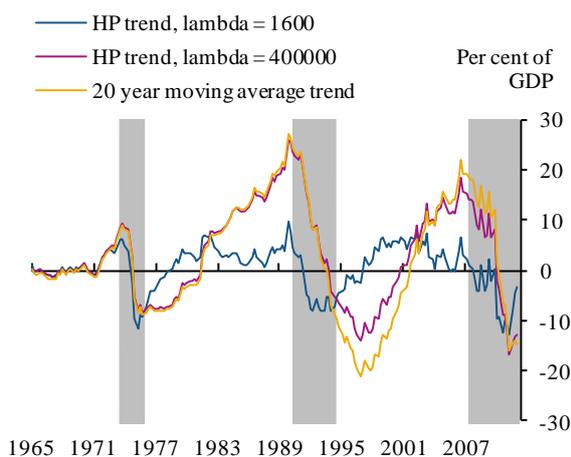
Is this the case in the UK? Chart 4 shows that the credit gap calculated using a two-sided filter is indeed very different from the one-sided one. But, as van Norden (2011) argues, it does not follow that this will be a source of policy error. What matters is whether the real-

¹¹ The two-sided filter chooses a trend that minimises a function of the deviations of the trend from the data series and the variation in the trend growth rate for every point on the trend line. As more data points are added, previous estimates of the trend line will be updated to reflect the new data. In contrast, a one-sided filter produces a trend line which is purely backward looking.

time credit gap estimates are useful for policymakers and our analysis above suggests that they are. In fact, Drehmann *et al.* (2011)'s cross-country analysis shows that even if policymakers did have the final credit gap estimates in real-time, it is not clear that they are a better leading indicator of crises. Analysis in Borgy *et al.* (2009) suggests that the one-sided filter leads the two-sided filter because, for the same smoothing parameter, it is influenced more by the latest observation and hence more pro-cyclical. But since the trend lags the actual observations, this implies that the credit gap crosses the one-sided trend earlier than the two-sided trend, making the credit gap based on the one-sided trend more useful as a leading indicator. Chart 4 shows that UK policymakers might indeed have found the real-time credit gap more useful in the build-up of the late 1980s and mid-2000s credit boom as it signalled the rapid credit expansion somewhat earlier.

We have also checked the robustness of our results with regard to the choice of trend. Aikman *et al.* (2010) suggest that credit cycles are substantially longer than business cycles, supporting the use of a smoothing parameter of 400,000 in the HP filtering. However, to understand how the indicator varies with different assumptions about the credit cycle, we calculated the trend with different smoothing parameters between 1,600 (usually assumed for the business cycle) and 400,000. If the credit cycle is a medium-term phenomenon (i.e. longer than 10 years in length), then using a parameter which assumes a much higher frequency is unlikely to yield good results; nonetheless it is a useful robustness check. While our analysis suggests that the power of the credit gap as an indicator is reduced when using lower smoothing parameters, the results in broad terms still stand. The same applies to different de-trending techniques, for example setting the trend equal to the line of best fit over the preceding twenty years (Chart 5). This is in line with Borgy *et al.* (2009) whose results on the whole do not differ materially between different methods to calculate the trend.

Chart 5: Credit-to-GDP gaps calculated with different trends^{(a)(b)}

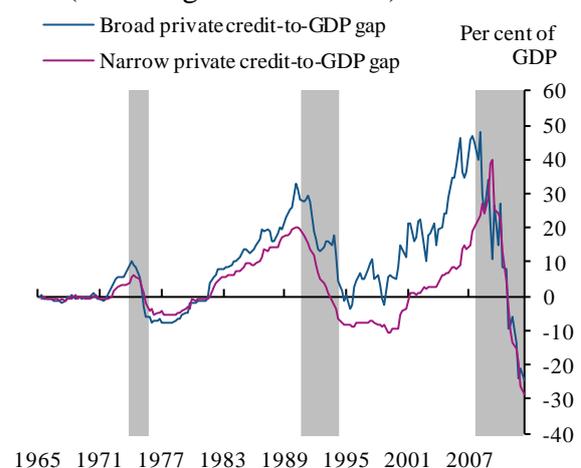


Source: ONS, Bank of England and Bank calculations.

(a) The credit-to-GDP gap is calculated as the percentage point difference between the credit to GDP ratio and its long-term trend, where the trend varies as above.

(b) Please see Chart 1 footnote (b) for the definition of credit.

Chart 6: Gap of broad and narrow total private credit-to-GDP relative to long-term trend (including intra-financial)^{(a)(b)(c)}



Source: ONS, Bank of England and Bank calculations.

(a) The credit-to-GDP gap is calculated as in footnote (a) in Chart 1.

(b) Broad credit including intra-financial credit is defined here as debt claims on the UK private sector. It comprises broad credit (as defined in Chart 1 footnote (b)) and loan, debt security and deposit obligations of non-bank financial institutions (NBFIs). ONS data on NBFIs are not available before 1997. Before then, stable

relationships between the ONS NBFI debt data and Bank of England data on lending to other financial corporations are assumed. (c) Narrow credit including intra-financial credit comprises narrow credit as defined in Chart 1 footnote (c) and UK-resident monetary financial institution sterling and foreign currency lending to other financial corporations.

Challenge iii): The definition of credit

We argued above that for the UK the credit gap based on both narrow and broad series of credit to the private non-financial sector work well. The advantage of a broad series is that it captures a wider range of sources of credit while the narrow series in the UK appears more accurate and goes back further in time.

In addition to the private non-financial sector, intra-financial lending played an important role ahead of the current crisis in the UK (Chart 6). A reason for excluding intra-financial system exposures particularly from broad series is that lending from banks might go to households via another intermediary and might therefore be counted twice if intra-financial credit was included. However, Gai *et al.* (2011) show that greater complexity may contribute to time-varying fragility in a financial network model. It may therefore be important to consider intra-financial system lending in its own right or include it in the credit measures used to calculate the credit gap.

3 Other indicators complementing the credit-to-GDP gap

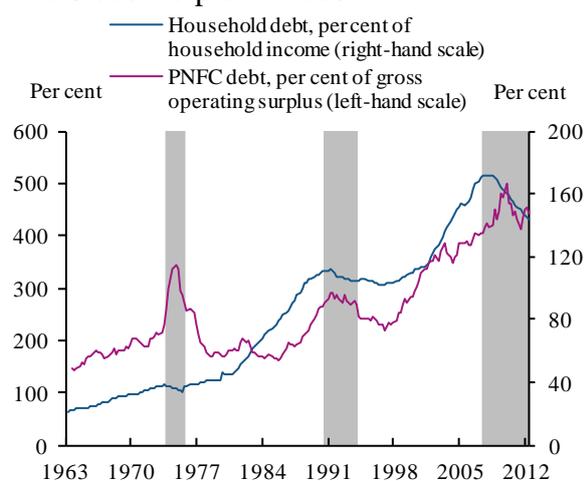
The credit-to-GDP gap conveys an overall sense of the change in indebtedness of the economy. But additional information including on the aggregate level of indebtedness and indebtedness of different sectors is needed in order to form a view on how likely this is to pose a threat to the financial system. This section discusses some areas where other indicators may complement the credit-to-GDP gap, drawing on cross-country literature where appropriate.

Complement i): What about levels?

The credit gap measure assumes that policy would want to be agnostic about the *level* of credit in the economy. Recent research has, however, shown that the level may also matter. With higher levels of leverage, the economy is more vulnerable to shocks and the deflationary effect of subsequent deleveraging may be greater (Koo, 2008, Reinhart and Rogoff, 2009). Furthermore Arcand *et al.* (2012) and Cecchetti and Kharroubi (2012) show that there is an inverse U-shape relationship between financial system growth and economic growth. This suggests that the absolute level of the credit-to-GDP ratio in itself would be of interest to policymakers. In addition, it may be helpful to look at sectoral splits to understand where exuberance might be building. For example, household debt-to-income and PNFC debt-to-profits might be helpful in this regard. Chart 7 indicates that both would have signalled increasing vulnerabilities in the UK prior to past crises. That said, UK households have experienced little financial distress so far in this crisis given the exceptionally low level of short-term interest rates and high incidence of floating rate mortgages (Bank of England (2011a)).

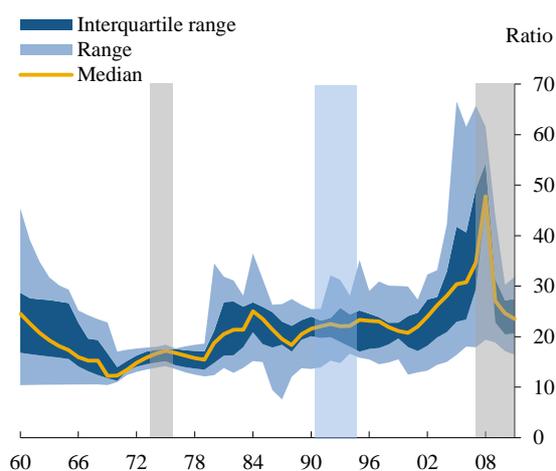
Household debt-to-income ratios have also tended to increase prior to crises in other advanced economies. For example, Mian and Sufi (2009) highlight the importance of household debt in the US financial crisis, finding that US areas with a high share of subprime borrowers experienced very rapid house price appreciation and growth in mortgage debt before the crisis and very high default rates during the crisis. In subsequent (2011) work, they have found that the decline in consumption was much stronger in counties with high household leverage and conclude that the ‘household balance sheet channel was responsible for a very large fraction of the decline in consumption during and after the recession’.

Chart 7: Household debt-to-income and PNFC debt-to-profit ratios^(a)



Source: ONS, Bank of England and Bank calculations.
(a) Gross debt as a percentage of a four-quarter moving sum of disposable income and gross operating surplus of the respective sector. ONS data on household and private non-financial corporate (PNFC) debt are used from 1989 due to limited data availability. Before then, a stable relationship is assumed between the ONS debt data and the Bank of England lending data. The household disposable income and corporate gross operating surplus series are adjusted for financial intermediation services indirectly measured (FISIM).

Chart 8: UK banks' leverage^{(a)(b)}



Source: Published accounts
(a) Ratio of total assets to shareholders' claims.
(b) The data are a backwardly consistent sample of institutions providing banking services in the United Kingdom in 2011. The sample includes the following financial groups: Barclays, HSBC, LBG, National Australia Bank, Nationwide, RBS and Santander UK. Where data are consistently available for the UK component of the banking group, these have been used. Northern Rock and Bradford and Bingley were included in the chart up to 2007 and 2008 respectively.

Complement ii): The sources of credit matter

The credit-to-GDP gap is also silent on the sources of credit. However, the way lending is funded is important. A highly leveraged financial system is likely to be more fragile than one based on less leverage because there will be less equity to absorb losses materialising on banks' assets. At the same time, greater maturity transformation, for example when credit is funded by high levels of short-term wholesale debt, is likely to make the financial system more prone to liquidity crises. This highlights the importance of measures speaking to the resilience of bank balance sheets.

For example, the leverage ratio of individual firms has been found to be a particularly useful indicator in this regard prior to the current crisis and the system-wide leverage ratio picked up sharply in the mid 2000s (Chart 8). Risk-based capital ratios also speak naturally to banking system resilience but were less helpful in differentiating between banks which ended up failing before the most recent crisis (see Haldane and Madouros (2012)). Moreover, the

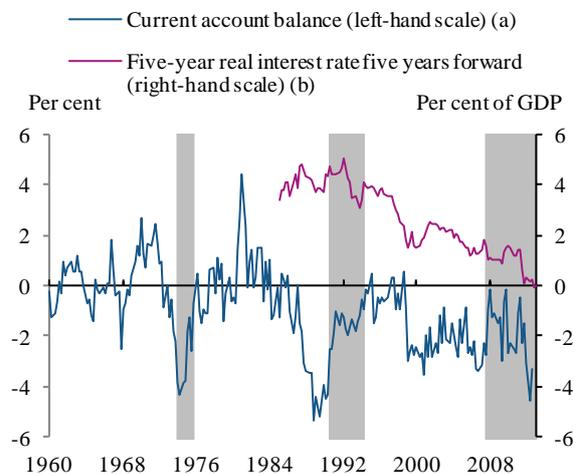
leverage ratio has been found to be an informative early warning signal of crises in OECD countries by Barrell *et al.* (2010).

Chart 9: Loan to deposit ratio^(a)



Source: Bank of England and Bank calculations.
 (a) Sterling lending to deposit ratio is calculated as M4Lx divided by retail deposits.

Chart 10: Current account balance and long-term real interest rate^{(a)(b)}



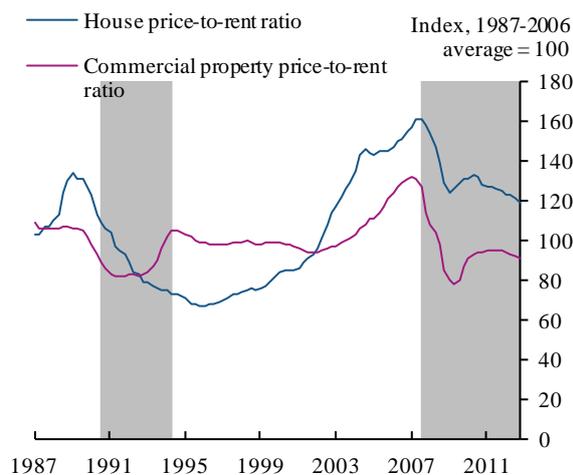
Sources: ONS, Bloomberg and Bank calculations.
 (a) As per cent of quarterly GDP.
 (b) 5 year real interest rates 5 years forward, derived from the Bank's index-linked government liabilities curve.

The flightiness of banks' funding also matters. Shin and Shin (2011) and Hahm *et al.* (2012), for example, emphasise the role of growing non-core liabilities as a source of financial instability. A high and increasing loan-to-deposit ratio would then signal a weakening in banks' funding. Rising loan-to-deposit ratios were evident in many countries prior to this crisis, including the UK (Chart 9), and the indicator also performed well in signalling impending distress in some of the countries which suffered crises in East Asia in 1997-8.

Credit booms may then be funded by capital inflows from abroad. The resilience of the domestic banking system would be undermined if it received foreign funding which turned out to be flighty. If foreign lending was directly extended to end-users but domestic banks took part in excess lending, resilience might also weaken. Large and persistent current account deficits are therefore also often seen as a warning sign of building vulnerabilities (see e.g. Barrell *et al.* (2010), Reinhart and Reinhart (2008)). Chart 10 shows that the UK ran a current account deficit before the current and the small banks' crisis. But countries with current account surpluses are also not automatically isolated from banking crises because their banks may hold risky claims on deficit countries.

Capital inflows might lead to low (real) long-term interest rates which in turn might fuel excessive risk-taking via a search for yield. Borgy *et al.* (2009) have found that a decrease in the long-term interest rate increases the probability of asset price booms. But real interest rates may also be driven by other developments, making them harder to interpret. While the real interest rate was low in the UK ahead of the current crisis, reflecting in part a global saving glut that may have contributed to the crisis (see Bernanke (2005), Astley *et al.* (2009), King (2009)), this was not the case prior to the small banks' crisis (Chart 10).

Chart 11: Real estate indicators^{(a)(b)}

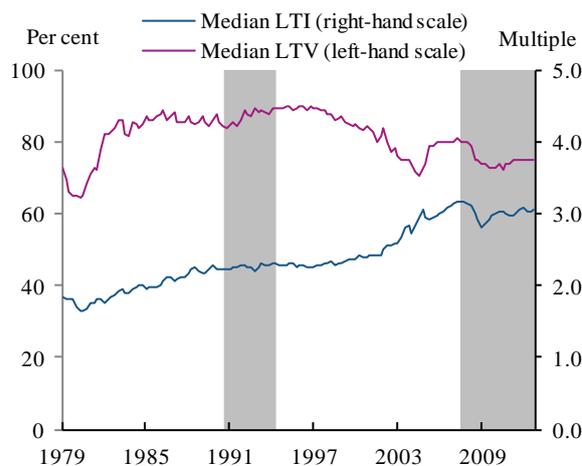


Sources: ONS, Nationwide, Halifax, Investment Property Databank (IPD) and Bank calculations.

(a) The residential house price-to-rent index is the ratio between an average of the Halifax and Nationwide house price indices and RPI housing rent.

(b) The commercial property price-to-rent index is the ratio between the IPD All Property Capital Growth Index and IPD All Property Rental Value Index.

Chart 12: Residential mortgage loan-to-value and loan-to-income ratios^(a)



Sources: FSA Product Sales Database, CML and Bank calculations.

(a) Excludes remortgagors.

Complement iii): The quality of credit matters

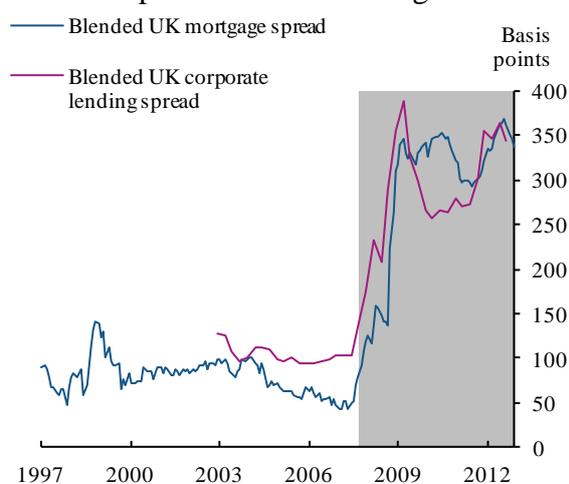
Besides the sources of credit, the uses of credit and the terms at which it is provided may also matter. For example, credit growth may be less of a concern for financial stability if it was used to finance investment projects that enhance the economy's capacity to produce output than if it was used to buy existing assets. House prices have typically been linked to financial crises (see, among others, Barrell *et al.* (2010), Drehmann *et al.* (2010), Claessens *et al.* (2011), Mendoza and Terrones (2008) and Riiser (2005)) and they tend to lead volume-based credit indicators. In the UK, peaks of the deviation of house prices relative to their long-term trend as well as relative to incomes and rent have tended to lead episodes of banking system distress over past decades (Chart 11). Loan-to-income multiples in new mortgages also picked up ahead of the current crisis. But while loan-to-value ratios were a good leading indicator of stress in the United States ahead of the current crisis, they remained below their long-run average before 2007 in the UK (Chart 12). High loan-to-value mortgages are likely to be more risky in the US than in the UK because several states in the US protect borrowers from personal liability if a property is foreclosed and sold at less than the mortgage value.

Equity prices, on the other hand, tend to do less well in signalling financial stress as suggested in our analysis for the UK and as documented in Drehmann *et al.* (2011). While Kaminsky and Reinhart (1999) and Borio and Lowe (2002) find some evidence that the stock market can be a useful indicator for banking crises, there are also shown to be more false signals than from other indicators. Not all equity price bubbles lead to widespread financial stress (e.g. dotcom crash) and equity markets may be sensitive to business cycle movements.

But if credit was used to speculate in rising equity markets as for example in the Great Depression, this would clearly be a cause for concern.

Lending spreads (Chart 13) may help to differentiate between demand and supply conditions in credit markets: before a crisis, we would expect spreads to be low if risk premia were unsustainably compressed due to exuberant credit supply (e.g. before the current crisis), whereas they may be at normal levels if credit growth reflected a greater balance between demand and supply factors (e.g. before the secondary banking crisis and the small banks' crisis). An advantage is that they are available in a timely manner. However, judging what is meant by 'unsustainably low' spreads is not straightforward.

Chart 13: Spreads on new lending^{(a)(b)}

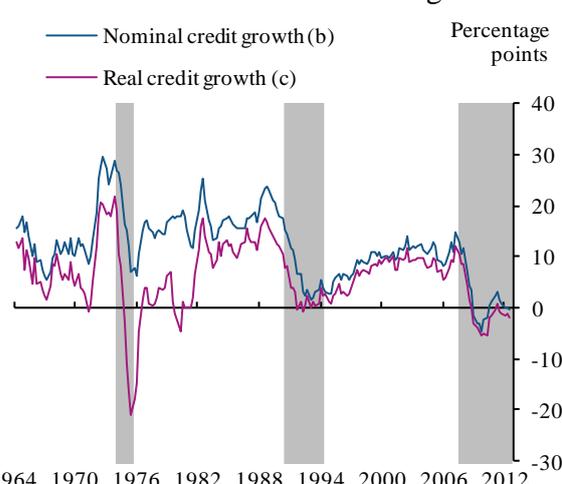


Source: Bank of England, Council of Mortgage Lenders, British Bankers' Association, Bank of America Merrill Lynch, de Montfort University, Bloomberg and Bank calculations.

(a) The mortgage spread is a weighted average of quoted mortgage rates over safe rates, using 90% LTV 2-year fixed rate mortgages and 70% LTV tracker, two- and five-year fixed rate mortgages. Spreads are taken relative to gilt yields of matching maturity for fixed rate products until August 2009, after which spreads are taken to OIS of matching maturity. Spreads are taken to Bank Rate for the tracker product.

(b) The corporate lending spread is a weighted average of UK investment grade company bond spreads to gilts (adjusted for any embedded option features such as convertibility into equity), SME lending rates to Bank Rate and CRE lending rates to Bank Rate.

Chart 14: Real and nominal credit growth^(a)



Source: ONS, Bank of England, Thomson-Reuters Datastream and Bank calculations.

(a) Twelve-month growth rate of nominal credit.

(b) Credit is defined here as debt claims on the UK private non-financial sector. This includes all liabilities of the household and not-for-profit sector and private non-financial corporations' loans and debt securities excluding derivatives, direct investment loans and loans secured on dwellings.

(c) Real credit growth is deflated using the GDP deflator.

Complement iv): The release phase

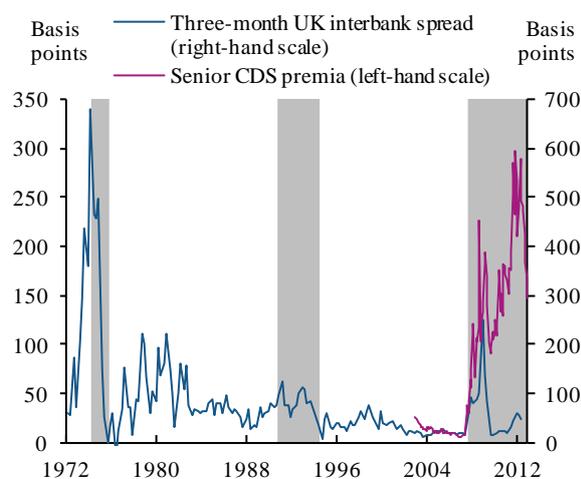
BCBS (2010) suggests that the countercyclical capital buffer should be released when the credit cycle turns. Chart 1 suggests that besides being a reasonable indicator for exuberance in credit growth, the credit-to-GDP gap would also have indicated the turning of the credit cycle in the UK. However, it may not be a timely indicator for policy easing in all circumstances. For example, Drehmann *et al.* (2011) show that the credit-to-GDP gap is slow to decline once crises materialise. A potential reason for this finding is that the stock of credit may not fall immediately in a downturn because corporates may have undrawn credit lines available. Also GDP growth may fall, potentially even leading to an increase in the ratio. The growth rate of credit variables may provide a more timely alternative to the credit

gap in identifying turning points of the financial cycle. Evidence presented in Drehmann *et al.* (2011) suggests that credit growth tends to reverse prior to the onset of stress – a finding which is in line with evidence from past episodes of banking system distress in the UK (Chart 14). In addition, an increase in lending spreads might indicate a tightening of credit conditions and might be a useful signal to ease policy.

Bank of England (2013) argues, however, that a downturn in the credit cycle alone is not sufficient for easing policy. In addition, information on banks’ resilience in the form of capital adequacy and market-based indicators is required. While the former give the policymaker an understanding of banks’ ability to absorb prospective losses from any remaining threats and support lending during a downturn, the latter give an indication on whether markets would allow banks to reduce their capital ratios to increase lending. Measures of banks’ profitability may also be informative because profits allow banks to build capital and are their first line of defence to absorb losses.

If banks’ balance sheets appear resilient, banks’ debt spreads remain low and banks’ equity prices do not fall markedly, policy easing might be appropriate. However, when market-based indicators such as banks’ debt spreads increase sharply signalling concerns over banks’ solvency, this might not be the time to release capital buffers. Indeed, in such circumstances it may be more appropriate for banks to increase *levels* of capital which may lead to a reduction in funding costs (see Bank of England (2013)). For the UK, CDS premia and interbank spreads rose sharply at the beginning of the current crisis (Chart 15). Gropp *et al.* (2002) and Drehmann *et al.* (2011) also find that bank credit spreads tend to coincide with stress events. This conditionality on stress materialising or not makes it difficult to test indicators for release in practice, particularly on time series when the macroprudential policy regime was not in operation.

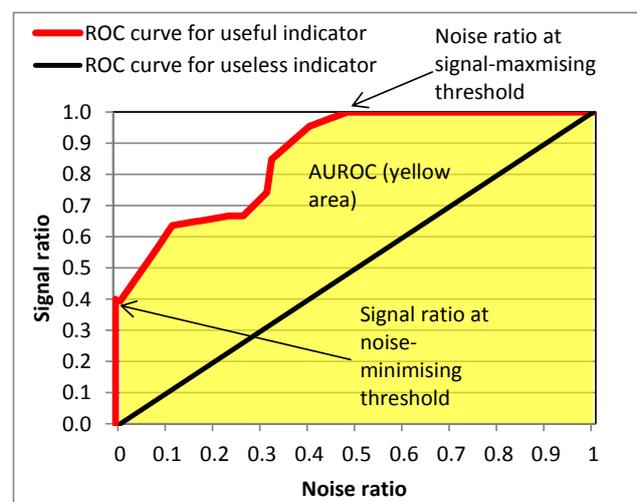
Chart 15: Bank funding spreads^(a)



Sources: Markit Group Limited, published accounts and Bank calculations.

(a) Average of major UK banks’ five-year senior CDS premia, weighted by end-year total assets. Includes Nationwide from July

Chart 16: ROC curve for useful and useless indicators



4 Comparison of different indicators

In this section, we conduct a simple analysis of the relative usefulness of some of these indicators in the UK context. We limit the analysis to those indicators for which we have data covering at least the three past episodes of banking system distress. For each indicator, we use quarterly data from 1969 Q1 until 2009 Q1¹². In the analysis, we take a non-parametric approach, evaluating indicators by their ability to provide good signals of forthcoming crises and to avoid false alarms. There are various different ways to use this information to rank indicators. As discussed below, we choose three criteria: the area under the receiver operator characteristic curve (AUROC), the signal ratio at the threshold which minimises the noise ratio and the noise ratio at the threshold that maximises the signal ratio. These rankings should be treated with appropriate caution given the low number of episodes of banking system distress in our sample. In future, we seek to extend this methodology to a larger set of countries, notwithstanding the potential drawbacks of this approach highlighted above.

A perfect early warning indicator of financial crises from a policymaking perspective would emit a signal ahead of every crisis and at no other time. To be useful to a policymaker, it must emit this signal sufficiently far in advance of a crisis for mitigating actions to be implemented and to have an effect.¹³ With this in mind, we have categorised the observations for each indicator thus:

- A: If an indicator is above a threshold value and a crisis occurs at any time between one year afterwards and four years afterwards, the observation is categorised as a good signal. As a result, there are twelve potential good signals for each banking crisis, giving 36 possible signals overall, rather than just one for each of the three crises (although these are, of course, not independent observations). This is meant to capture the intuition that a persistent signal may be more valuable to a policymaker than a signal that just flashes once before a crisis. That said, there may be

¹² The leverage series we have is annual so we interpolated it to obtain quarterly data.

¹³ BCBS (2010) suggests that policymakers preannounce an increase in the countercyclical capital buffer by twelve months. Of course, one hopes that policy will be able to prevent risk building to the levels at which crises are likely.

diminishing marginal returns to signals ahead of any one crisis. To capture this, we give more weight to the first four quarters for which a signal is emitted than to any following observations ahead of a period of stress (the first is weighted by a five, the second by a four,...the fifth and any others by a one). This weighting is of course arbitrary and could be developed in future work.¹⁴

- B: If an indicator is below a threshold value and a crisis occurs at any time between one year afterwards and four years afterwards, the observation is categorised as a missed signal (type 1 error).
- C: If an indicator is above a threshold value and a crisis does not occur at any time between one year afterwards and four years afterwards, the observation is categorised as a false alarm (type 2 error).
- D: If an indicator is below a threshold value and a crisis does not occur at any time between one year afterwards and four years afterwards, the observation is categorised as a good silence.

Note that as the threshold chosen changes, the values for A to D will change (a higher threshold will be associated with higher values for B and D, missed signals and good silences, and lower values for A and C, good signals and false alarms).

Two more methodological points are worth highlighting. First, we have chosen each indicator in such a way that theory would lead us to expect a high value of the indicator to presage a crisis and a low value the absence of crises. This meant reversing the sign of some variables (e.g. we used the current account deficit, not the current account balance). Second, to prevent an observation from being called a good signal or false alarm during or in the year preceding a crisis, we exclude these observations.

As the numbers of crisis and non-crisis observations are fixed, we can condense these summary statistics further into the signal ratio, $SR = \frac{A}{A+B}$, and the noise ratio, $NR = \frac{C}{C+D}$, without losing any relevant information. Note that with 36 potential crisis signals (twelve of which have a weight greater than one), SR and NR can take a wide range of values rather than just 0, $\frac{1}{3}$, $\frac{2}{3}$ and 1, as would be the case if indicators could only have a single binary signal in relation to each of the three crisis episodes. For any given threshold, the policymaker would prefer an indicator with a high signal ratio and a low noise ratio. However, there will be a trade-off between these two desirable features. For low thresholds, both the signal ratio and the noise ratio are likely to be high as the indicator emits signals most of the time. The opposite scenario applies for high threshold values. If costs of macroprudential interventions are low and benefits high, policymakers may prefer a low threshold value to avoid type 1 errors rather than type 2 errors.

¹⁴ The weighting scheme does not have marked impacts on the AUROC, signal ratio and noise ratios shown in Table 1 below. The AUROCs and signal ratios tend to be somewhat higher, and noise ratios somewhat lower, with the weighting scheme. It has little bearing on the relative performance of the indicators against these metrics.

The receiver operating characteristic (ROC) curve summarises this trade-off. It plots the noise ratio against the signal ratio. As the threshold value falls, both the noise and the signal ratio rise, so the ROC curve slopes upwards. The ROC curve associated with a useless indicator (i.e. an indicator for which the probability of a crisis if the indicator exceeds a threshold is equal to the unconditional probability of a crisis) would be a 45 degree line, as shown in the chart¹⁵. A perfect indicator would give no signals above a high threshold (i.e. zero signal and noise ratios), only signals below a low threshold (i.e. signal and noise ratios equal to one) and neither type I nor type II errors in between (i.e. a signal ratio equal to one and noise ratio equal to zero). In other words, it would trace out the left hand and top edges of the chart above. Indicators which are useful to policymakers lie significantly above the 45 degree line (e.g. the red line in the chart).

Our first criterion for ranking the indicators, the area under the ROC curve (AUROC), does not rely on any particular choice of threshold. Rather, it summarises the degree to which the signal ratio exceeds the noise ratio for *all* thresholds. An indicator with an AUROC equal to one would be a perfect early warning indicator (the whole of the chart above would be under the ROC curve), while a useless indicator would have an AUROC equal to a half (half the chart above is under the 45 degree line; see Chart 16). In general, the higher is an indicator's AUROC, the more useful it will be for a policymaker.

In our calculations, we have approximated the AUROC by: (i) plotting the noise and signal ratios for the maximum and minimum observed value of the indicator in question and nineteen points in between; (ii) calculating the trapezoidal area under the curve for each of the twenty resulting intervals (equal to the product of the change in the noise ratio and the average signal ratio); and (iii) aggregating. The AUROC is shown as the shaded area in Chart 16.

The second and third criteria – the signal ratio at the noise-minimising threshold and the noise ratio at the signal-maximising threshold – are also marked on Chart 16. The second criterion would be chosen by a policymaker who seeks to minimise type 2 errors, while the third criterion would be chosen by a policymaker who seeks to minimise type 1 errors. In future work, we plan to model policymaker preferences over type 1 and type 2 errors. This would allow us to choose optimal thresholds for each indicator and then rank the indicators by their ability to satisfy these preferences.

As well as calculating these three statistics, we also derive their statistical significance using the recursive bootstrap method (MacKinnon, 2006, is a very helpful guide). Each indicator is modelled as an AR(ρ) process where ρ is chosen using the Schwartz Information Criterion. The residuals from each of these regressions are then rescaled by a hat matrix to ensure that their variance is unbiased. These are sampled randomly and, together with the coefficients

¹⁵ A useless indicator has the following properties: $Pr(I > T|C) = Pr(I > T)$ and $Pr(I > T|\neg C) = Pr(I > T)$, where I is the indicator value, T is the threshold and C is a crisis. For a useless indicator, $SR = \frac{Pr((I>T)\cap C)}{Pr(C)} = \frac{Pr(I>T|C)*Pr(C)}{Pr(C)} = Pr(I > T)$ and $NR = \frac{Pr((I>T)\cap \neg C)}{Pr(\neg C)} = \frac{Pr(I>T|\neg C)*Pr(\neg C)}{Pr(\neg C)} = Pr(I > T)$, so the signal and noise ratios are equal.

from the AR(ρ) regressions, are used to construct bootstrap samples. The actual AUROCs, signal ratios at the noise-minimising threshold and noise ratios at the signal-maximising threshold are then compared to the same statistics for the bootstrapped series. The ranking of the actual statistics in the distributions for the simulated data gives the p value.

This method works for autoregressions for which the residuals are not heteroskedastic. For some indicators, this is not the case. In these cases, we use the recursive wild bootstrap. This is the same method, except that the residuals are kept in the same order but multiplied by random draws from the Rademacher distribution (1 with $p=0.5$, -1 with $p=0.5$).

Table 1 shows the results. The credit gap indicators tend to perform reasonably well, with high and statistically significant AUROCs. The signal ratios at the noise-minimising threshold are all statistically significant and comfortably above zero, while the noise ratios at the signal-maximising threshold are reasonably low and statistically significant. The precise sectors covered do not make a lot of difference in this sample. Nor does the choice between broad and narrow credit. This is not surprising, as they are highly correlated. The flow-based credit measures tend to perform less well than the gap metrics, with real growth rates of credit outperforming nominal growth rates, though not by much.

Of the other indicators, the real house price gap performs particularly well, with the highest AUROC of the whole sample. That said, it might not be very useful for a policymaker who cares a lot about type II errors (because the signal ratio at the noise-minimising threshold is low and insignificant). The equity price gap and leverage ratio do not perform well.

Table 1: Comparing indicators through AUROC, minimum noise and maximum signal ratios^(a)

Indicator	Ranking method	AUROC	Minimum noise ratio		Maximum signal ratio	
			Threshold	Signal ratio	Threshold	Noise ratio
AGGREGATE GAPS						
Broad HH and PNFC credit gap		0.87*	12.5	0.39**	-2.7	0.48**
Narrow HH and PNFC credit gap		0.84*	9.4	0.33**	-1.4	0.44**
Broad HH, PNFC and OFC credit gap		0.79	22.9	0.41**	-2.3	0.79*
Narrow HH, PNFC and OFC credit gap		0.87**	13.6	0.45**	-2.3	0.51**
AGGREGATE GROWTH RATES						
Nominal broad HH and PNFC credit growth		0.69	26.4	0.08	7.9	0.84
Nominal narrow HH and PNFC credit growth		0.71	24.2	0.08	8.6	0.73*
Nominal broad HH, PNFC and OFC credit growth		0.74	24.8	0.14	8.0	0.88
Nominal narrow HH, PNFC and OFC credit growth		0.73	25.5	0.14	8.9	0.69**
Real broad HH and PNFC credit growth		0.77	19.8	0.08	-1.6	0.95
Real narrow HH and PNFC credit growth		0.81**	17.8	0.21**	-0.4	0.90
Real broad HH, PNFC and OFC credit growth		0.82**	17.2	0.35**	-1.0	0.95
Real narrow HH, PNFC and OFC credit growth		0.79*	19.9	0.14	-0.4	0.93
OTHER INDICATORS						
HH DTI gap		0.85*	15.7	0.50**	-1.7	0.63
PNFC DTP gap		0.82*	68.6	0.00	-20.0	0.48**
OFC credit-to-GDP gap		0.60	23.5	0.21	-0.4	1.00
Current account deficit		0.67	3.9	0.18*	-3.0	0.99
Loan-to-deposit ratio gap		0.78	0.1	0.32**	0.0	0.85
Leverage ratio		0.48	26.4	0.30**	12.2	1.00
Real house price gap		0.88**	33.7	0.21	-3.5	0.58**
Real commercial property price gap		0.83*	15.0	0.53***	-4.3	0.80
Real equity price gap		0.32	110.7	0.00	-34.8	0.98
Corporate bond spread		0.61	3.2	0.00	0.0	1.00

Source: ONS, Bank of England, Thomson-Reuters Datastream, Investment Property Databank, Global Financial Database, Halifax,

Nationwide, published accounts and Bank calculations.

(a) *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

5 Using the indicators in practice: a case study

We have argued above that more than one indicator is required to set the countercyclical capital buffer. This begs the question of how the dominant signal that should guide policy might be extracted from the set of indicators. There are different ways to combine information from different indicators, including statistical approaches that allow for weighting different indicators, ‘heatmaps’ that rely on thresholds and pure judgement. Regarding the former, principal component analysis or logit regressions may for example be used to combine indicators. Heatmaps that assign a colour to each indicator depending on the indicator’s signal as defined by statistical rules may be a useful visualisation device regarding the overall message from the set of indicators. However, an element of judgement is still required in any approach as the importance of different indicators may vary over time and further information, such as market or supervisory intelligence, would also be important. A set of indicators should be seen as the starting point for analysis. If indicators in this set flag an issue, this should be investigated further.

Both Switzerland and Norway have opted for a ‘guided discretion’ approach with neither relying on a purely mechanical relationship between indicators and setting the CCB.¹⁶ In a similar spirit, the UK’s interim FPC notes in Bank of England (2013) that “the greater the degree of imbalance as measured by the core indicators, the more homogeneous the picture that the different indicators convey, and the more consistent that picture is with market and supervisory intelligence, the more likely it is that the FPC will adjust the CCB and SCRs in response”.

The remainder of this section discusses the signals given in late 2003 by some of the indicators discussed in this paper. We choose 2003 in order to understand whether the indicators were useful in signalling unsustainable credit growth and threats to resilience well ahead of the start of the current crisis. Overall, the indicators gave a mixed signal.

The Basel III credit-to-GDP gap stood at 9.1% in Q4 2003, which under the Basel III guidance would have translated into a buffer of almost 2.5%. Including intra-financial credit doubles the gap. The Basel III gap had grown rapidly in the preceding years, reaching a peak in Q3 2003, but declined in the last quarter of 2003. While the rapid increase in the early 2000s provided a clear signal of exuberant credit conditions, the decline in Q4 2003 might have given pause for thought. Nominal credit was growing at above 10% on the previous year in late 2003 and had been growing at this pace for a number of years. While high, this was not particularly high compared with the growth observed before the small banks’ crisis in the early 1990s. This is, however, where the level of the series also matters: the growth rates observed might not have given a strong signal of being unsustainable in any particular quarter given historical evidence, but the indebtedness of the economy was growing given persistent growth. In terms of ratios, household debt to income was at an all-time high and PNFC debt-

¹⁶ See Swiss National Bank (2013) and Norges Bank (2013).

to-profit close to its peak, although it decreased somewhat through 2003. This pattern was reflected in property prices as well: while residential house prices were booming, the commercial real estate market had cooled somewhat.

This rise in the economy's indebtedness started to show in banks' balance sheets: banks' leverage picked up in 2003, but remained within the bounds of historical observations and banks increased reliance on non-core funds with the loan-to-deposit ratio back at the highs seen prior to the small banks' crisis. Banks' profitability strengthened as lending spreads ticked up and banks' CDS premia fell. The change in these indicators may have signalled a strengthening in banks' resilience at the time rather than an emerging underpricing of risk: banks' profits had taken a dip and CDS premia had increased the year before.

The current account deficit narrowed in late 2003 but the deficit had persisted for a number of years, contributing to growing stock imbalances. The real long-term interest rate was stable around 2.25%, up from lows observed in the late 1990s and 2000-1 and hence by itself not suggestive of a search for yield or the need for policy tightening.

While credit conditions could, on balance, have been judged to be buoyant in late 2003 and in preceding quarters, and there was some evidence that banks' funding structures were becoming less stable, the indicators did not suggest significant underpricing of risk in a historic context. These are exactly the conditions under which market and supervisory intelligence and policymaker judgement are critical: Bank of England (2003) notes that market contacts describe some investors as willing to take more credit, interest rate or exchange rate risk in order to increase returns in the short run, i.e. an early indication of search for yield behaviour. By 2005, the indicators themselves were painting a more homogenous picture and would have given a clear signal of unsustainable credit conditions and material threats to banks' resilience.

6 Conclusion

This paper reviews the performance in the UK of the credit-to-GDP gap proposed under Basel III for the countercyclical capital buffer. We find that irrespective of criticisms, it provided timely signals for policy tightening over the past 50 years in the UK.

We also discuss how to complement the credit gap in the UK context. In particular, we find that flow- and market-based indicators may complement the credit gap for decisions to release the countercyclical capital buffer. Other indicators, such as property prices and sectoral credit ratios, may give an indication of what projects the lending is used to finance and hence of its quality. Indicators related to property prices were particularly important during past credit cycles in the UK. In addition, indicators related to banks' balance sheets, e.g. leverage ratio or loan-to-deposit ratios, would be needed to understand how a credit boom is funded.

But further work in this area is required: we do not understand well how indicators will change as policy is implemented, i.e. to what extent Goodhart's law is likely to apply.

Moreover, our knowledge on the counterfactual path of the economy if the signals from the indicators are heeded is limited. And in the future, if macroprudential policy is successful in reducing the frequency and severity of financial crises, assessing the usefulness of indicators cannot rely on whether the indicators forecast crises. Finally, our analysis focused on indicators for setting capital tools. Indicators for other macroprudential tools, such as liquidity or structural tools, would also need to be developed.

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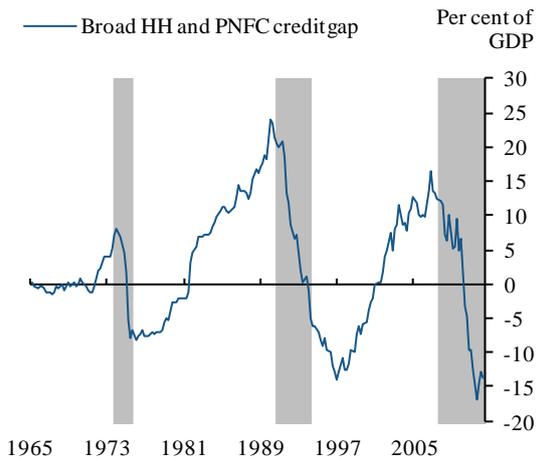
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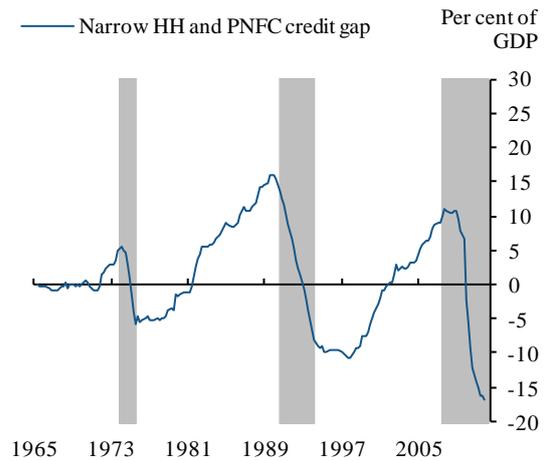
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Broad HH and PNFC credit gap



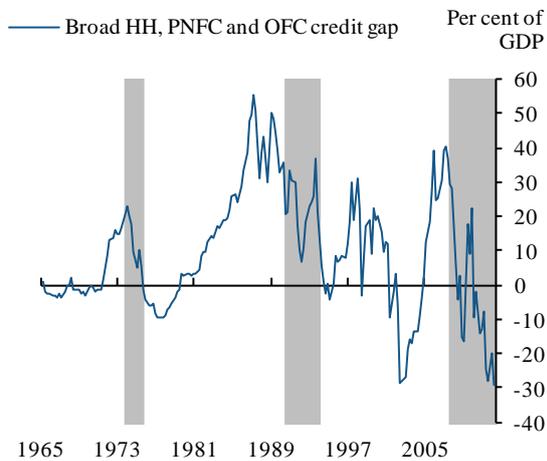
Source: ONS, Bank of England and Bank calculations.

Narrow HH and PNFC credit gap



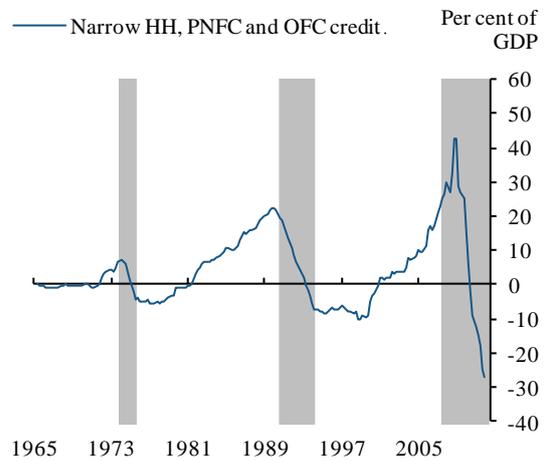
Source: Bank of England and Bank calculations.

Broad HH, PNFC and OFC credit gap



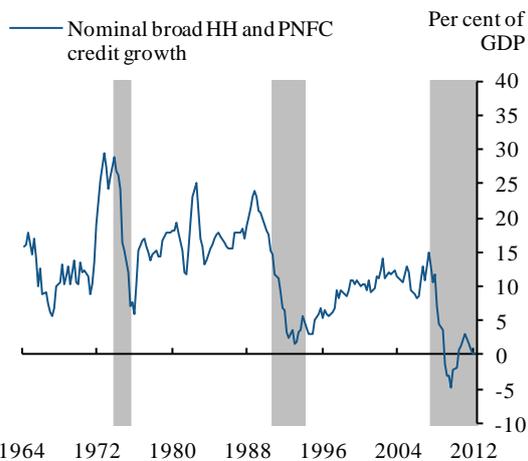
Source: ONS, Bank of England and Bank calculations.

Narrow HH, PNFC and OFC credit gap



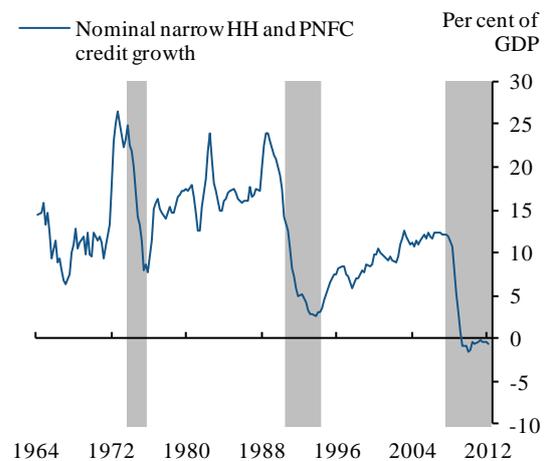
Source: Bank of England and Bank calculations.

Nominal broad HH and PNFC credit growth



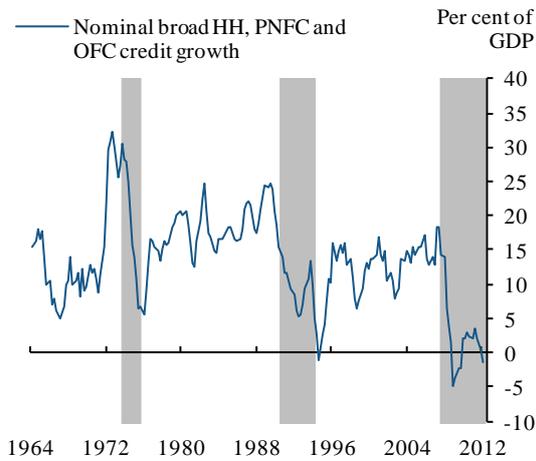
Source: ONS, Bank of England and Bank calculations.

Nominal narrow HH and PNFC credit growth



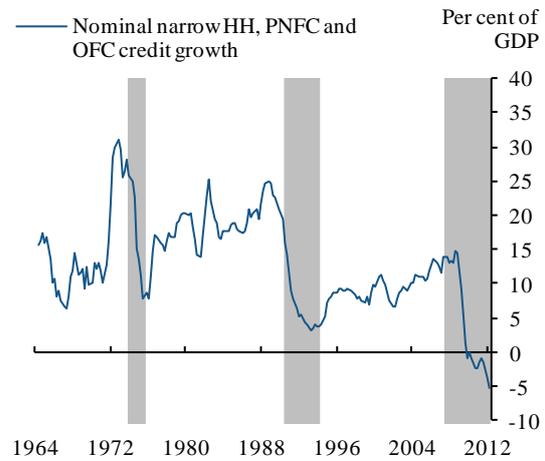
Source: Bank of England and Bank calculations.

Nominal broad HH, PNFC and OFC credit growth



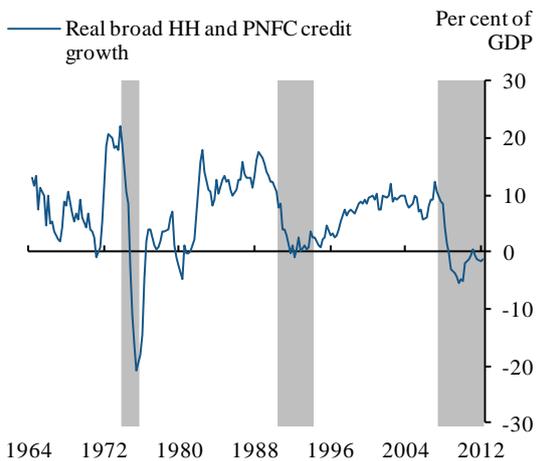
Source: ONS, Bank of England and Bank calculations.

Nominal narrow HH, PNFC and OFC credit growth



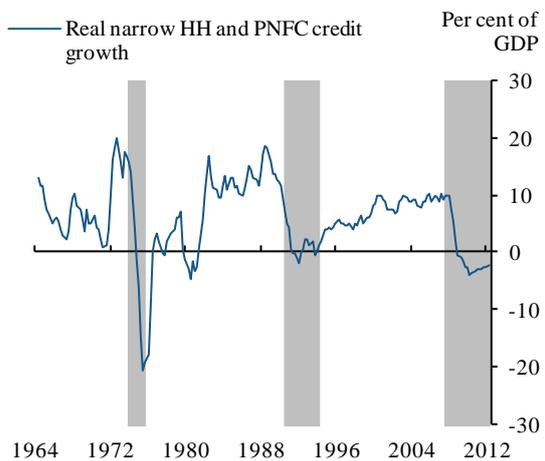
Source: Bank of England and Bank calculations.

Real broad HH and PNFC credit growth



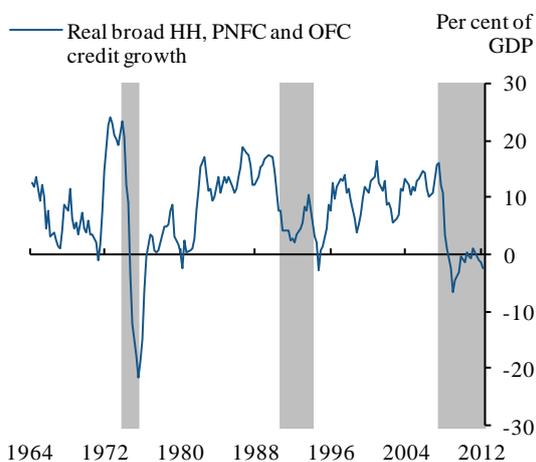
Source: ONS, Bank of England and Bank calculations.

Real narrow HH and PNFC credit growth

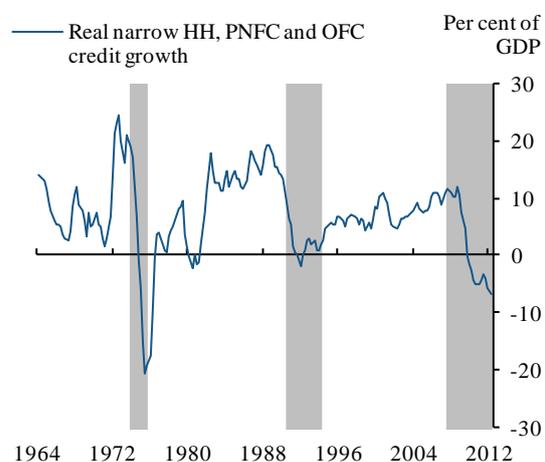


Source: ONS, Bank of England, Thomson-Reuters Datastream and Bank calculations.

Real broad HH, PNFC and OFC credit growth

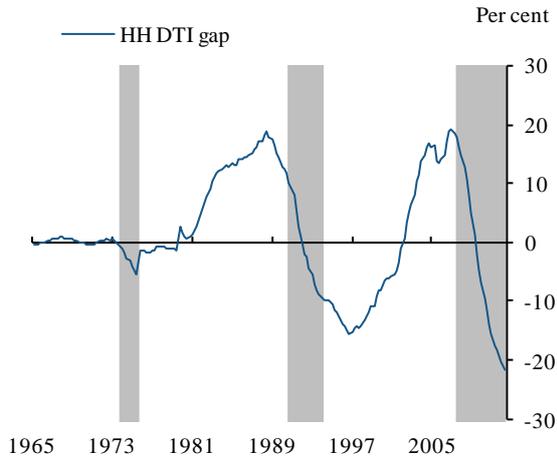


Real narrow HH, PNFC and OFC credit growth



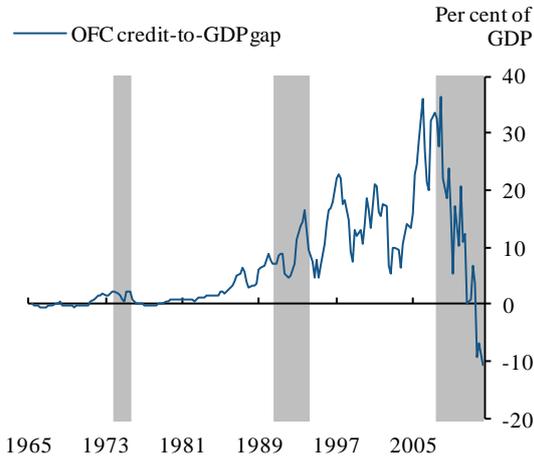
Source: ONS, Bank of England, Thomson-Reuters Datastream and Bank calculations.

HH debt-to-income gap



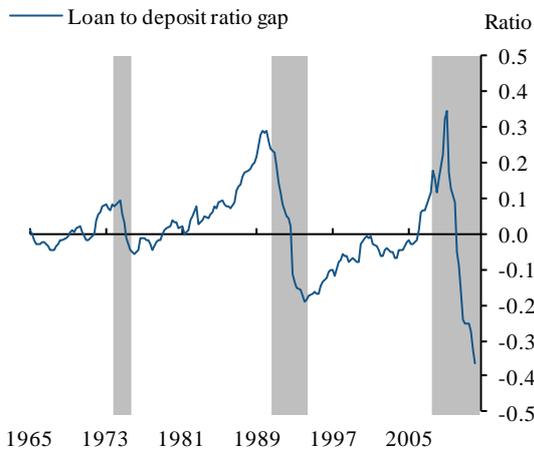
Source: ONS, Bank of England and Bank calculations.

OFC credit-to-GDP gap



Source: ONS, Bank of England and Bank calculations.

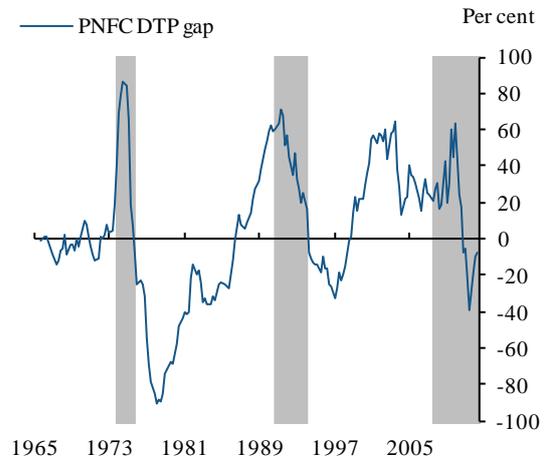
Loan to deposit ratio gap



Source: Bank of England and Bank calculations.

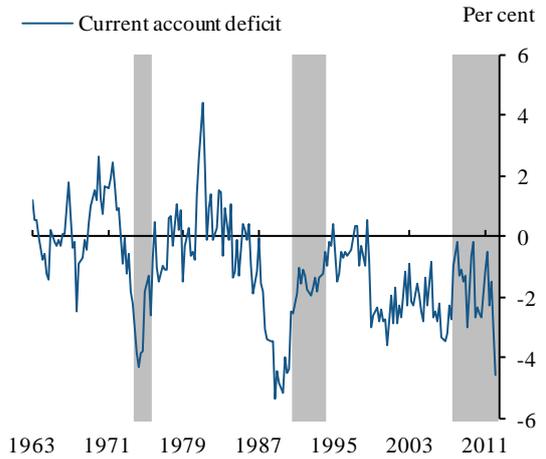
Source: Bank of England, Thomson-Reuters Datastream and Bank calculations.

PNFC debt-to-profit gap



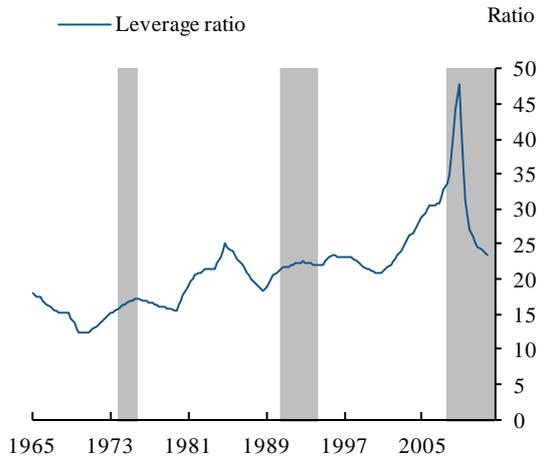
Source: ONS, Bank of England and Bank calculations.

Current account deficit



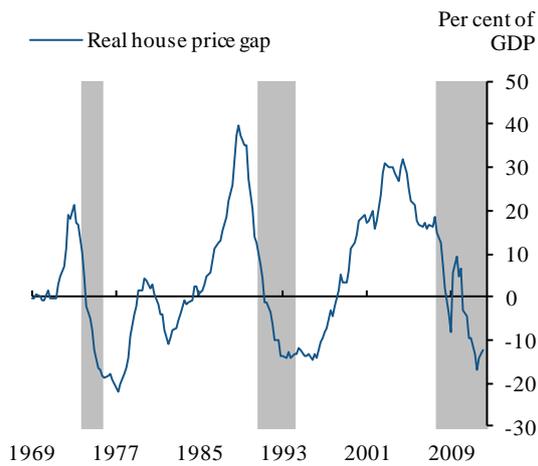
Source: ONS and Bank calculations.

Leverage ratio



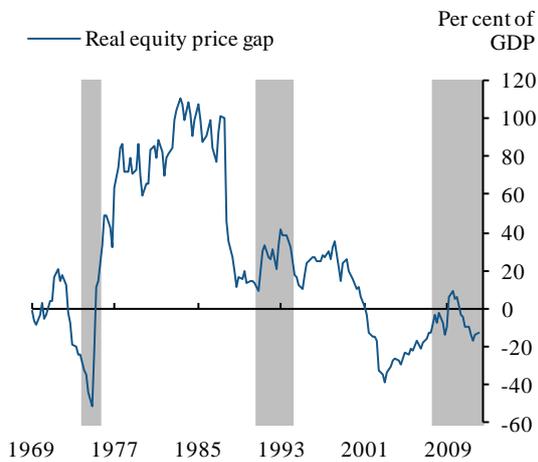
Source: Published accounts and Bank calculations.

Real house price gap



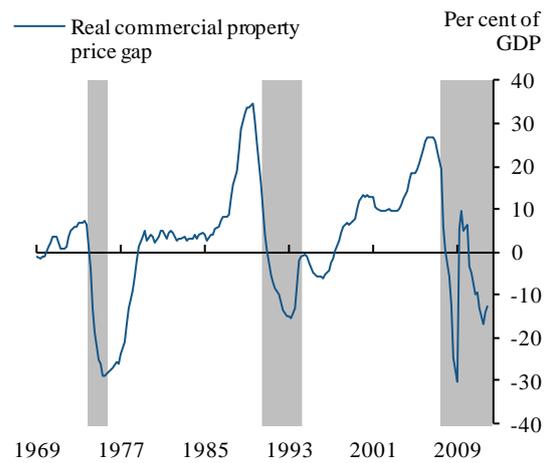
Source: Nationwide, Halifax and Bank calculations.

Real equity price gap



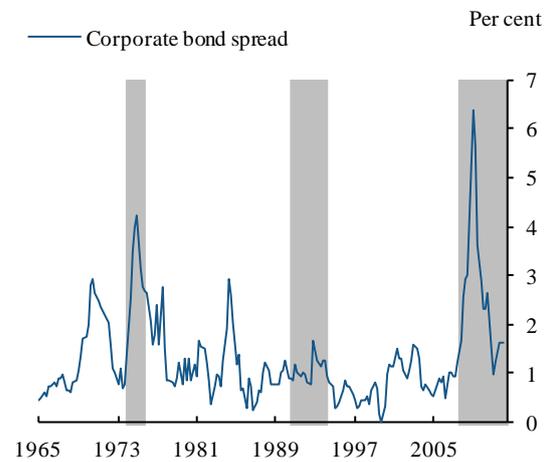
Source: Thomson-Reuters Datastream and Bank calculations.

Real commercial property price gap



Source: Investment Property Databank and Bank calculations.

Corporate bond spread



Source: Global Financial Database and Bank calculations.