The provisioning experience of the major UK banks: a small panel investigation

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Abstract

Using panel regression analysis, the paper investigates what factors may help to explain increases in loan-loss provisions for the major UK banks. Explanatory variables reviewed include aggregate variables such as GDP growth as well as bank-specific factors such as the composition of the loan portfolio. The main findings are that a number of macroeconomic variables can indeed inform about banks' provisions, in particular real GDP growth, real interest rates and lagged aggregate lending growth. Bank-specific behaviour is also important — increased lending to riskier sectors, such as commercial property companies, has generally been associated with higher provisions.

Summary

Ideally, banks' provisions should capture expected losses. In practice, accounting conventions in the United Kingdom mean that provisions are set in a backward rather than forward-looking manner — specific provisions can only be made once the debt is shown to have genuinely become impaired and general provisions should cover losses that exist in the current loan portfolio but have yet to be identified. Provisions therefore correspond largely to realised loan losses.

Broadly speaking, the major UK banks' provisions ratios have moved quite closely together in the past. Most banks experienced a significant increase in provisions in the early 1990s — coinciding with a period of economic recession in the United Kingdom — while the provisions ratio fell back in the mid-1990s. Some important differences in movement are apparent. In particular, some of the major UK commercial banks experienced significant defaults on their Latin-American debts in the late 1980s. However, stripping out these problem country effects, provision ratios tended to vary more across time than across banks. This would seem to suggest that, over this period, the major UK banks' provisions arose more often from shocks hitting the banking sector as a whole than from idiosyncratic risks.

Banks' own behaviour may contribute to their vulnerability to such disturbances. In particular, banks may be prone to underestimate future losses in periods of economic expansion as lending criteria are relaxed or because concentrations of loan exposures increase. During subsequent economic downturns, this 'overlending' gives rise to a sharp increase in bad debts. As this may occur when bank income is itself weaker due to slower loan demand growth, such losses can actually reduce banks' existing capital. Further, during such recession periods banks may themselves be less able to raise new capital.

This paper investigates the possible influences on UK banks' loan-loss provisions (as a proxy for realised losses). Specifically, based on a small (unbalanced) panel dataset covering the period 1978–2000, regression analysis is used to examine the influence of macroeconomic variables and bank-specific factors on reported bad debt provisions. The main findings are that real GDP growth, real interest rates and lagged aggregate lending can indeed inform about banks' provisions. But bank behaviour is also important. In particular, increased lending to riskier sectors, such as commercial property companies, has generally been associated with higher provisions.

1. Introduction

Banks make charges against profits and reduce the value of loans recorded in their balance sheets when they have reason to believe that borrowers will default on those loans. Such loan-loss provisions are typically one of the first quantitative indicators of deterioration in loan quality and, at the same time, a key contributor to fluctuations in bank profits and capital. Understanding the determinants of provisions is therefore important in assessing financial stability.

In principle, provisions should be forward-looking — they should relate to future expected losses on loans.⁽¹⁾ In practice, accounting conventions in the United Kingdom (and indeed in a number of other countries) mean that provisions are set in a backward rather than forward-looking manner — specific provisions can only be made once the debt is shown to have genuinely become impaired and general provisions should cover losses which have not yet been identified but which currently lie latent in the loan book. That is, provisions reflect actual, rather than expected losses, which may take some time to reveal themselves.

Moreover, experience suggests that banks are often surprised by the size of losses they incur (ie the *ex post* credit risk is greater than expected). In the United Kingdom, this has meant that banks have in the past had to make unexpectedly large provisions against profits, which in turn have typically led to debt write-offs. Banks may be particularly prone to underestimate future losses in periods of economic expansion as lending criteria are relaxed or because concentrations of loan exposures increase. During subsequent economic downturns, this 'overlending' gives rise to a sharp increase in bad debts. As this may occur when bank income is itself weaker due to slower loan demand growth, such losses can actually reduce banks' existing capital. Further, during such recession periods banks may themselves be less able to raise new capital.

Both features — backward-looking provisioning and the potential for 'overlending' during economic booms — suggest that banks' losses are likely to exhibit counter-cyclical behaviour. That is, as macroeconomic conditions deteriorate and borrowers face difficulties servicing their debts, recognised credit losses will tend to increase. The aim of this paper is to investigate these cyclical influences on UK banks' loan-loss provisions (as a proxy for realised losses) in more detail. Specifically, based on a small (unbalanced) panel dataset covering the period 1978–2000, regression analysis is used to examine the influence of macroeconomic variables such as GDP and interest rates on reported bad debt provisions. At the same time, I investigate how far bank-specific factors such as the composition of the loan portfolio can also explain UK banks' loan-loss experience.

The rest of the paper is organised as follows. Section 2 describes the basic stylised facts about UK banks' provisioning experience over the past 20 years or so. This period covers one full economic cycle and at least part of another. Hopefully therefore, the patterns will be suggestive of the macroeconomic influences on provisions. Section 3 describes the types of empirical models I investigate and Section 4 discusses the regression results. A review of the robustness of the empirical results is undertaken in Section 5, while Section 6 offers some concluding remarks.

⁽¹⁾ For a detailed exposition of the conceptual issues relating to loan-loss provisioning see Borio and Lowe (2001).

2. Some stylised facts about UK banks' provisions

This section explores the available empirical evidence on the major UK banks' provisioning and write-off experience to establish the relevant stylised facts. These in turn should help to motivate the formal empirical modelling work undertaken in Section 4.

2.1 Description of the dataset

The dataset consists of individual institution data drawn largely from the published annual accounts of eleven major UK banks.⁽²⁾ Specifically, accounting data were collected on both balance sheet and profit and loss information for these banks. For expositional reasons, the sample of banks is divided into commercial banks — those traditional UK high street banks whose loan portfolios include a wide array of personal and business lending — and mortgage banks — those banks who were previously building societies but who have demutualised. The distinction between commercial and mortgage banks is becoming increasingly fuzzy as the business profiles of the two groups have moved closer together. Nonetheless, the distinction is probably still helpful because their loan portfolios remain sufficiently different. For example, lending secured on residential property still accounts for on average around 80% of mortgage banks' total domestic loans and advances compared with around 30% for commercial banks. Moreover, disclosure practices meant that long time series for provisions, write-offs etc were typically only available for the traditional UK commercial banks. Specifically, the accounting data were available for most commercial banks from 1978, with the exception of recoveries in the case of NatWest, who reported write-offs net of recoveries for 1986 to 1991. For mortgage banks they were generally available only from 1987, although even then there are some gaps in the flow figures between 1987 and 1991.

2.2 Patterns in the data

2.2.1 UK mortgage and commercial banks

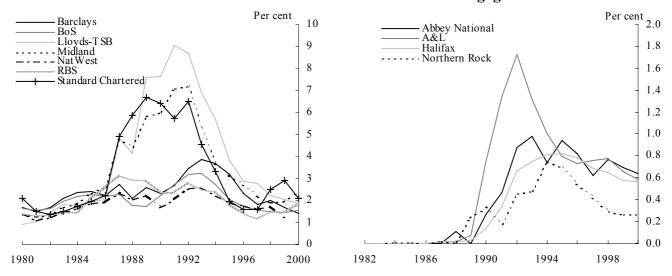
Charts 1 and 2 plot the time series for the stock of loan-loss provisions relative to total loans⁽³⁾ for each of the banks in the sample. On average, the stock of provision-to-loans ratio is much smaller for the mortgage banks than the commercial banks. This is not surprising given the typically lower level of risk associated with secured, residential mortgage lending. Over the period 1987–2000, the provisions ratio for commercial banks averaged 3.2% compared with 0.6% for the mortgage bank group.

⁽²⁾ The banks are: Barclays, Bank of Scotland (BoS), Lloyds-TSB, Midland, NatWest, Royal Bank of Scotland (RBS), Standard Chartered (UK commercial banks) and — Abbey National, Alliance & Leicester, Halifax and Northern Rock (UK mortgage banks). In 1992, HSBC banking group acquired Midland bank but continued to report separate accounts for Midland, albeit under a new name HSBC bank PLC. Figures for the period after 1992 refer to HSBC bank PLC.

 $^{^{(3)}}$ The total stock of loans is measured gross — ie before provisions are deducted.

Chart 1: Stock of provisions-to-loans ratio^(a) — UK commercial banks

Chart 2: Stock of provisions-to-loans ratio^(a) — UK mortgage banks



(a) Defined as the stock of loan-loss provisions expressed as a percentage of total loans and advances to customers.

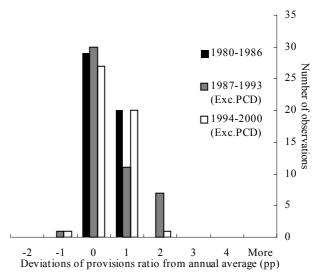
Broadly speaking, the major UK banks' provisions ratios tend to move together quite closely. Within both peer groups, most banks experienced a significant increase in provisions in the early 1990s — coinciding with a period of economic recession in the United Kingdom — while the provisions ratio fell back in the mid-1990s. But some important differences in movement are also apparent. For example, Midland, Lloyds and Standard Chartered experienced sharply rising provisions before the onset of the economic recession in the late 1980s and their peak in the provisions ratio in the early 1990s was much higher than other banks in their peer group.

Much of this cross-bank variation seems to be related to these banks' exposures to developing countries that experienced serious liquidity problems in this period — a number of the major UK commercial banks experienced significant defaults on their Latin-American debts in the late 1980s (see Box 1). Indeed, stripping out these problem country effects, provision ratios tended to vary more across time than across banks. The first column in Table 1 shows the extent to which banks' average stock and new charge provisions ratios varied over the 1987–2000 period. The coefficient of variation for the stock of provisions relative to loans — the standard deviation in any year from the whole-period average — was 0.4 for commercial banks and 0.6 for mortgage banks. In contrast, the variation in provisioning across banks, on average, over the period was much lower — the coefficient of variation across commercial banks was only 0.2 and 0.3 for mortgage banks. This would seem to suggest that over this period the major UK banks' provisions arose more often from shocks hitting the banking sector as a whole than from idiosyncratic risks.

Table 1: Coefficient of variation in UKbanks' provisions-to-loans ratio 1987–2000^(a)

Stock of	Average of bank peer group over time	Across banks, average over time
provisions/loans Commercial banks Mortgage banks	0.4	0.2
New provisions	0.0	0.5
charge/loans Commercial banks Mortgage banks	0.7 1.1	0.1 0.4

Chart 3: Deviations of stock of provisions-to-loans ratio from annual average over different periods — UK commercial banks



(a) Standard deviation divided by mean, excluding PCD provisions.

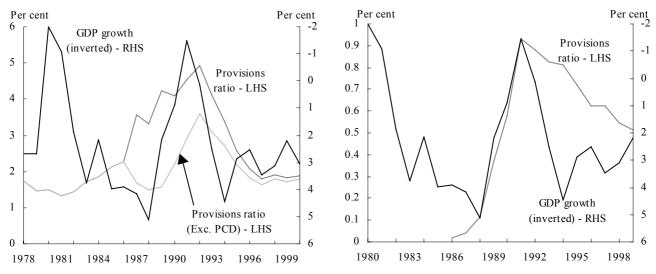
That said, provisions are more variable across banks in different time periods. Chart 3 plots the distribution of percentage point deviations from the average commercial bank stock of provisions (excluding problem-country debt (PCD) provisions) to loans ratio for three separate time intervals. Over the period 1980–86, the provisions ratio was very similar across the seven commercial banks included in the sample. But the distribution of the provisions ratio widened between 1987 and 1993, before falling again over the period 1994–2000. Specifically, the coefficient of variation was 0.2 in the period 1980–86, rose to 0.5 between 1987–93 before falling back to 0.3 in the period 1994–2000. Similarly, for the mortgage banks, the Alliance & Leicester's stock of provisions to loan ratio peaked at around 1.8% of loans, almost double the peak level of other mortgage banks. This seems to suggest that different characteristics of the banks' businesses and in particular the risk profile of their loan books is also a factor behind their different loss experience. For example, liberalisation in financial markets during the late 1980s meant that UK commercial banks entered a number of new markets and lent to different types of borrower. This could have made them particularly vulnerable to increased credit losses when the domestic recession hit.

2.2.2 Provisioning and the economic cycle

Charts 4 and 5 plot the average total stock of provisions-to-loans ratio for the commercial banks and mortgage banks respectively against annual UK real GDP growth. For both groups of banks there is evidence that provisions exhibit some cyclical dependence, but the relationship between provisioning and the cycle is not stable over time. This is most obvious for the commercial banks where longer runs of data are available. The provisioning ratio peaked shortly after the trough in output during the early 1990s downturn and decreased as the economy recovered. However, the provisioning ratio did <u>not</u> increase significantly during the early 1980s recession.

Chart 4: Stock of provisions-to-loans ratio and UK GDP growth — average UK commercial banks

Chart 5: Stock of provisions-to-loans ratio and UK GDP growth — average UK mortgage banks



There are a number of potential reasons why the provisioning experience during the two economic downturns was different. In particular, there were different levels of corporate/personal indebtedness in the periods before the two downturns. The expansion of the corporate and personal sector balance sheets in the late 1980s undoubtedly made these sectors more vulnerable to the sharp tightening in monetary policy in the early 1990s. Moreover, regulatory changes (ie deregulation and financial liberalisation) may have contributed to 'excessive' loan growth in the late 1980s in the sense that banks took on greater credit risk than they realised.

The proximate 'causes' of the recessions were also different (ie a high real exchange rate in the first, a sharp increase in interest rates in the second recession). Therefore different sectors of the economy were more severely hit by the slowdown in aggregate demand during the two recessions. Davis (1993) examined sectoral lending data of one major UK bank and found that the average provisions-to-loan ratio was higher in all sectors of the economy over the period 1989–98 compared with 1979–88. But provisions for bad loans were particularly high in some sectors, in particular those related to property such as construction and commercial real estate lending.

2.2.3 General and specific provisions

In the United Kingdom, and indeed in most other countries, the accounting standards distinguish between specific and general provisions. The nature of this distinction, however, is not standardised across countries. Moreover, in the United Kingdom at least, the accounting rules are sufficiently vague that banks have significant discretion about how exactly they determine their specific and general provisions. (See Box 2.)

Broadly speaking, specific provisions are made against individual loans (or pools of loans) that can be identified as having become impaired. That is, they refer to loans where the risk from non-repayment has increased sharply following some default event (such as overdue payments).

They are more akin to *ex post* (ie realised) credit losses since specific provisions are only raised when the credit risk event has occurred and not in anticipation of the event.

In contrast, general provisions can, in principle, refer to *ex ante* expected losses that are related to future uncertain events. However, in most countries restrictions are placed on the maximum amount of general provisions that can be made. For example, in some countries, accounting/regulatory restrictions mean that general provisions are limited to a small percentage of total loans. And taxation arrangements often provide a disincentive to recognise expected losses through general loan-loss provisions even if accounting regulations permit. In almost all countries, bad loans are ultimately tax-deductible, either at the point when a provision is made or when the loan write-off actually occurs. But such tax-breaks are typically not available for general provisions thus providing no tax incentive to recognise potential losses earlier.

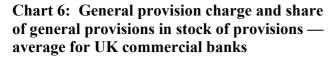
Furthermore, in the United Kingdom, a strict reading of the accounting standards would suggest that general provisions should be tied to losses actually existing in banks' loan books but which have yet to be identified. In this sense therefore, even general provisions in the United Kingdom are not especially forward-looking.

Specific provisions are typically larger than general provisions, especially for commercial banks. Over the period 1980–2000, commercial bank specific provisions accounted for nearly 70% of the total stock of provisions on average. Moreover, there is little evidence that UK commercial banks' general provisions rose in the late 1980s in recognition of potential future losses associated with higher risk borrowers taken on and/or the increased likelihood of a future downturn and its impact on borrowers' ability to service their debts.⁽⁴⁾ Indeed, general provisions fell in the late 1980s — as noted above, a number of the major UK banks made general PCD provisions in the early 1980s and some of these were subsequently released as debt workouts proceeded and as much larger specific provision charges were raised instead.

2.2.4 Provisions, write-offs and recoveries

In the normal course of events, loans will actually be written off from the balance sheet some time after a provision against the debt was originally raised. But some of a bank's losses are deemed to be immediately irrecoverable and are written off without a prior provision. Other losses that previously seemed to be irrecoverable and were written off actually recover (for example, because of the liquidation of collateral). And some provisions that were previously created will be released as the bank reassesses the likely loss following default. The accounts will record the net effect of all these movements in any period. That is, *the stock of provisions may fall because a large number of write-offs occur in the period, even though new provisions against bad debts may have risen significantly*.

⁽⁴⁾ Formally, if output is mean-reverting around a trend and is partly predictable, the conditional probability of a downturn increases the more that output rises above trend. Of course, if changes in economic activity are random, then banks may not have predicted significant future losses in the early 1990s. In this case, general provisions may not have been necessary even if banks do employ them in a forward-looking fashion.



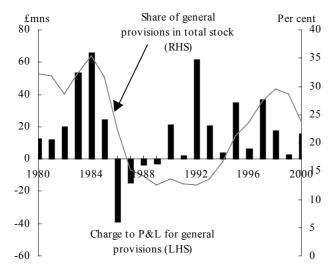


Chart 8: Write-offs and new provisions charge-to-loans ratio — average UK commercial banks

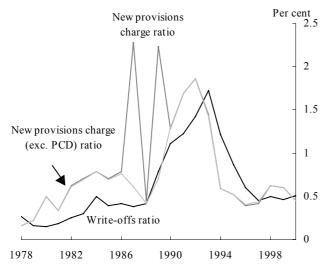
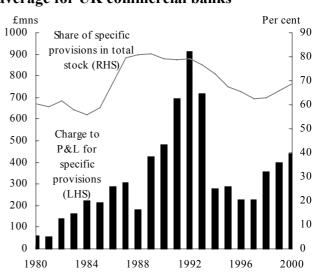


Chart 7: Specific provision charge and share of specific provisions in stock of provisions — average for UK commercial banks



It seems unlikely that banks systematically under or over-estimate provisions in relation to actual net write-offs. Chart 8 shows that average UK commercial banks loan-loss provisions charges against profits (as a proportion of total loans) were larger than loan write-offs (as a proportion of total loans) in some periods but over the whole 1980–2000 period they were close on average. Similarly, the empirical evidence for each of the major UK commercial banks suggests that the majority of the provisions signalled irrecoverable losses. Total cumulated write-offs (net of recoveries) covered around 90% of the total cumulated provisions of the major UK banks over the period 1978–2000. That said, there is some evidence that this 'coverage' ratio has increased over time — between 1978 and 1986 the percentage was nearer 70%.⁽⁵⁾

Bank	Cumulative write-offs divided by cumulative provisions charge			
	1978-2000	1978-86	1987-2000	
Barclays	0.87 (0.86)	0.66 (0.62)	0.91 (0.90)	
Bank of Scotland	0.81 (0.74)	0.53 (0.49)	0.83 (0.76)	
Lloyds-TSB	0.86 (0.75)	0.68 (0.55)	0.88 (0.78)	
Midland	0.85 (0.79)	0.66 (0.62)	0.91 (0.84)	
NatWest	1.07 (0.92)	0.68 (0.51)	1.13 (0.98)	
Royal Bank of Scotland	0.81 (0.92)	0.57 (0.43)	0.83 (0.96)	
Standard Chartered	N/A	0.53 (0.43)	0.95 (0.88)	
Abbey National	N/A	N/A	0.85 (0.85)	
Alliance & Leicester	N/A	N/A	0.91 (0.80)	
Halifax	N/A	N/A	0.81 (0.77)	
Northern Rock	N/A	N/A	0.91 (0.91)	

Table 2: Major UK banks' cumulative write-offs and provisions compared

Figures in brackets refer to write-offs net of recoveries.

In terms of the *timing* of the relationship between provisions and write-offs, the empirical evidence supports the view that write-offs typically occur quite soon after provisions have been charged against profits. Table 3 presents the results from a simple (pooled) regression model in which write-offs are a linear function of past (total) provision charges.⁽⁶⁾

⁽⁶⁾ Formally a distributed lag model of the form $y_{it} = \alpha + \sum_{q=0}^{\infty} \beta_q x_{it-q} + u_{it}$ was estimated where y_{it} is the amount

⁽⁵⁾ An alternative measure of loan quality is the proportion of the loan portfolio that is non-performing. Unlike in the US there are no prescriptive rules about how banks ought to measure and document non-performing loans (NPLs). Broadly speaking, NPLs refer to loans on which borrowers are in arrears on the interest and principal repayments and these loans are usually classified according to how far they are overdue. In addition to NPLs, some banks identify potential problem lendings. These are loans that are current as to the payment of principal and interest but where there exists serious doubt as to the ability of the borrower to comply with repayment terms in the near future. In the UK, there is no mechanical link between NPLs/potential problem lendings and loan-loss provisions because late payment of loans cannot be mapped systematically to default. Presumably evidence of arrears may sometimes trigger the recognition of a default event and so justify the creation of a provision, but this need not necessarily be the case. For example, Lloyds-TSB's non-performing loans have been less than their bad debt provisions in recent years and at the end of 2000 specific provisions represented over 140% of non-performing loans.

of loan write-offs by bank *i* as a proportion of its (gross) loans and advances and x_{it} is bank *i*'s loan-loss provisions charge against profits as a proportion of bank *i*'s (gross) loans and advances. The model pools the information across banks to establish the empirical link between loan-loss provisions and write-offs.

Table 3: Pooled regression where the dependent variable is ln(net write-offs/loans & advances) and the regressor is ln(provisions charge/loan & advances)

Dependent variable: ln(wo _t)	Including PCD provisions ⁽¹⁾		Excluding PCD provisions ⁽¹⁾	
	Regression 1	Regression 2	Regression 1	Regression 2
Constant	.001319	.0012473*	.0003992	.0005619
ln(prF _{t-1})	.1959715***	.1765435***	.6474195***	.6688654***
ln(prF _{t-2})	.2544544***	.2228726***	.0154836	0124726
ln(prF _{t-3})	.1478753**	.165547***	.1693638**	.1605185**
ln(prF _{t-4})		.0618546		.0103125
Test of parameter	chi2(40) = 74.51	chi2(50) = 87.67	chi2(40) = 59.50	chi2(50) = 66.41
constancy across	Prob>chi2= 0.0008	Prob>chi2 = 0.0008	Prob>chi2 = 0.0242	Prob>chi2 = 0.0600
banks				
Ho: Common coefficients				

***, **, * implies significant at the 1%, 5% and 10% significance levels.

(1) Based on panel-corrected standard errors in the presence of heteroscedasticity and autocorrelated residuals.

The regression results suggest that the long-run multiplier (ie the long-run impact of a unit increase in the provision charge-to-loans ratio) is around 0.8 for the series excluding PCD provisions. This seems to be the case even when different lag structures are employed. Therefore, around 80% of provisions would appear to be reflected in write-offs after around 3–4 years with a mean lag of around $1\frac{1}{2}$ years.⁽⁷⁾

Table 4: Correlation between write-offs and new provision charges

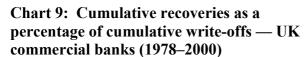
Bank	Correlation of write-offs with provisions lagged one period	Correlation of write-offs with provisions lagged two periods	Correlation of write-offs with provisions lagged three periods
Barclays	0.86*	0.70*	0.29
Bank of Scotland	0.97*	0.95*	0.75*
Lloyds-TSB	0.36	0.32	0.36
Midland	0.52*	0.63*	0.48*
NatWest	0.86*	0.72*	0.43
Royal Bank of Scotland	0.73*	0.71*	0.60*
Standard Chartered	0.41	0.43	0.16
* Implies significant at 95	% level		

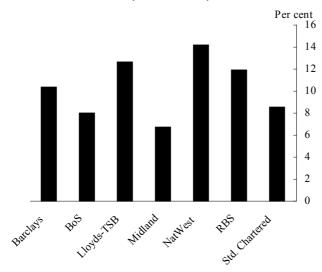
* Implies significant at 95% level.

However, the tests for slope parameter constancy indicate that the lag coefficients are likely to differ across banks. That is, the lagged relationship between new provisions and write-offs varies for each of the banks in the sample. This is especially true for the series *including* PCD provisions. Further evidence of this is shown in Table 4, which gives the correlation statistics between write-offs and lagged provision charges for the UK commercial banks. In most cases the correlation coefficient is around 0.7 or above with a lower coefficient when longer lags are applied to the provisions term. But it is much lower for some banks and indeed in some cases the correlation statistics are not significant. This cross-sectional variation seems likely to reflect different bank practices in writing off problem loans.

⁽⁷⁾ The rate of pass-through from provisions to net write-offs for the series including PCD provisions is lower at around 60%. This is consistent with the fact that a number of banks were able to securitise some of their PCD and these loans were therefore not included as write-offs.

Fewer details of recoveries are available from banks' published accounts, particularly for the mortgage banks. But those observations that are available suggest that recoveries are typically relatively small compared with write-offs. Specifically, in aggregate only around 10% of write-offs incurred by UK commercial banks were subsequently recovered over the period 1978–2000.





To summarise, past evidence on UK bank provisions suggest that:

- In the United Kingdom, most loan-loss provisions tend to be backward-looking banks raise provision charges when evidence of default surfaces and not in anticipation of such events.
- Banks in the United Kingdom have typically been affected by common shocks to the quality of their loan portfolios. In particular, a number of the major United Kingdom banks increased sharply their provisions charges around the time of the domestic recession in the United Kingdom in the early 1990s.
- Most bank provisions translate into actual write-offs a year or two later. And subsequent loan recoveries tend to be modest.

3. Modelling bank provisions

Since in practice provisions tend to be close actual write-offs they include both unexpected losses as well as the realisation of expected losses. Ideally it would be useful to disentangle provisions made for expected and unexpected losses since the latter might provide a better indicator of bank vulnerability. But to do so would require knowledge about the likely behavioural influences on banks provisioning practices and in particular the motives and payoffs to banks from pursuing particular provisioning, pricing and capital policies. Instead I focus here on the less ambitious task of modelling the links between a number of key macroeconomic and bank-specific variables and loan-loss provisions. Given that in the United Kingdom general provisions and specific provisions both relate to losses that are likely to already exist in bank loan portfolios, for the purposes of estimation I concentrate on trying to explain total loan-loss provisions. I motivate the choice of explanatory variables and the expected sign of the relationship with provisions by appeal to economic priors but do not seek to identify the underlying behavioural relationship between the variables.

In formal modelling terms, I estimate a reduced-form relationship rather than a structural model — the aim is to uncover the statistical linkages between key explanatory variables and banks' provisions/loan losses. That is, I posit a relationship between bank's provisions and a host of potential explanatory variables that I assume are exogenous or at least predetermined in relation to bank provisions. But such a relationship could be consistent with many structural models that describe how provisions and the other variables are *jointly* determined. The reduced-form model is helpful in addressing questions of the sort: what would happen to banks' provisions if loan growth fell by x%, but it will not definitively inform about *why* loan growth rates and provisioning rates move together. The relationship could arise for a number of reasons and to distinguish between them requires a structural model of the underlying behavioural relationship.

3.1 Model specifications

The basic estimation strategy is to pool the observations across banks and undertake regression analysis on the pooled sample. The advantage of pooling is that more reliable estimates of the parameters in the model may be obtained. It is a valid procedure if there is reason to believe that the relationship between the variables is stable across cross-section units. And the stylised facts above suggest that the in the past the major UK banks provisions seem to have responded to common shocks. But the disadvantage of pooling is that any heterogeneity across banks will reveal itself in the 'unexplained' residual terms, which has implications for the appropriate estimator (see below).

I posit two formulations for the regression analysis — a static and a dynamic model. In the dynamic specification, bank provisions are assumed to depend partly on their own past observations. Formally, I estimate:

$$y_{it} = \alpha + \beta(L)x_{it} + u_{it}, \ i = 1,...,Nt = 1,...,T$$
(1) (Static model)

$$y_{it} = \alpha + \sum_{s=1}^{S} \delta_s y_{i(t-s)} + \beta(L)x_{it} + u_{it} \ t = q + 1,...,T, i = 1,...,N$$
(2) (Dynamic model)

where y_{it} refers to provisions for bank *i* in period *t*,

 x_{it} refers to the observations on the potential explanatory variables,

 u_{it} is a random error term with distribution $N(0,\Sigma)$,

 $\beta(L)$ is a vector of associated polynomials in the lag operator, and

q is the maximum lag length in the model.

The choice between the two models should ideally be motivated by economic theory. In particular, do banks adjust their provisions slowly to recognise potential losses against loans following a default event as the dynamic model would suggest? Or is it more likely that a surprise increase in provisions in one year is followed by a surprise increase in provisions in the next year (perhaps because there may be some persistence in the underlying economic shocks that banks face) which could be consistent with the static model with serial correlation in the errors. To the extent that the accounting rules are at all definitive, they would suggest that banks recognise the full amount of any probable loss as soon as the default event occurs, which would perhaps argue for the static model. But equally, if banks' assessment of probable losses is updated based on new information each period then provisions could be systematically related

each period, which would argue for a dynamic specification. In the absence of a well-articulated theory about the dynamic adjustment of loan-loss provisions it is not clear that one specification should necessarily be preferred over the other. Consequently in the analysis below, I present results for both the static and dynamic models.

3.2 Estimation issues

Since the sample data are drawn from different UK banks, they will exhibit some cross-sectional variation. Both the static and dynamic regression models implicitly assume that the systematic influences on bank provisions are common across banks and consequently any heterogeneity is likely to show up in the 'unexplained' part of the model (ie the disturbance term). Simple OLS estimation procedures produce inefficient parameter estimates when the disturbance term is not well-behaved (ie a random, white noise error). However, procedures are available to adjust the standard errors derived from OLS estimation, so that correct inference is possible — for example, the White heteroscedastic estimator and the Newey-West autocorrelation consistent estimator. More generally, if a particular structure for the residual heteroscedasticity/correlation can be assumed, generalised least squares (GLS) estimation procedure can be applied.⁽⁸⁾ This procedure is adopted below for the static model.

The presence of the lagged dependent variable in the dynamic model causes particular difficulties for normal panel estimation procedures even when complex error structures are assumed and GLS procedures applied. This is because any time-invariant bank-specific effect, which shows up in the error term, will be correlated with the lagged dependent variable. As a result OLS and GLS procedures will produce biased and inconsistent coefficient estimates. To overcome this correlation between the errors and the lagged dependent variable, instrumental variable techniques can be applied. Specifically, following Arellano and Bond (1991), I use a generalised method of moments estimator which optimises across the available set of instruments to produce consistent parameter estimates for the dynamic model.

3.3 Potential explanatory variables

The combination of empirical evidence and economic theory suggest a number of factors that may be influential in explaining the development of problem loans in bank portfolios. These may be grouped into four classes:

(i) Macroeconomic influences on asset quality — the ability of borrowers to repay bank debt is likely to reflect the macroeconomic environment. Household and firms' cash flows/wealth will typically vary with the economic cycle and therefore so will their ability to service their debt. Moreover, the more heavily indebted are households and firms, the more likely that adverse macroeconomic shocks will lead to borrower default. For example, Davis (1993) found that increased indebtedness of firms increased the probability of bankruptcy

⁽⁸⁾ A particular example of a GLS estimator is the so-called random-effects model. This assumes that any individual unobserved bank-specific effects do not vary over time and can be separately identified in the overall regression error. That is: $u_{it} = \lambda_i + \varepsilon_{it}$ where $\varepsilon_i \sim iid(0, \sigma_{\varepsilon}^2)$, $\lambda_i \sim iid(0, \sigma_{\lambda}^2)$. This (one-way) error-components structure implies that the composite error term exhibits a particular form of autocorrelation. An alternative specification is the so-called fixed-effects model. This assumes that the bank-specific effect is fixed and can be estimated using an intercept dummy for each bank.

in a number of countries including the United States, United Kingdom and France. The impact of high debt levels may be particularly serious if debt happens to be concentrated in high-risk firms.⁽⁹⁾

The actions of banks can ameliorate the effects of macroeconomic disturbances, as might be the case if banks have well-established relationships with their customers that they want to preserve. During periods of slow growth or even recessions, banks may be prepared to alter the terms and conditions on loans to particular borrowers (eg maturity extensions, standstills, interest moratoria etc). However, anecdotal evidence suggests that there are limits on the extent to which banks are prepared to vary conditions that directly affect the risk profile of their own balance sheet (eg quality of the collateral, loan covenants). In particular, where the solvency of the customer is in question, banks often have less room for manoeuvre.

(ii) Asset price 'shocks' — Disturbances in asset markets can impair the value of banks' asset values. This effect is most easily observed on marketable instruments where assets are marked-to-market and any losses on investments are charged against profit. But asset price changes may also affect banks' loan portfolios. In particular, financial and real assets are often taken as collateral on loans. If asset prices fall, the value of collateral on loans will fall which could lead to greater levels of default. In the United Kingdom, the most notable example of this occurred with falls in nominal residential house prices in the early 1990s, which resulted in a number of borrowers experiencing so-called 'negative equity' in their property. To the extent that borrowers then subsequently defaulted, the collateral was insufficient to cover the debts and losses were incurred by banks on their loans.

Sharp changes in asset prices may also be associated with increased fragility of borrowers through more traditional macroeconomic channels. For example, sharp changes in interest rates can lead to cash-flow problems at firms and households, which in turn can lead to borrower default. Similarly large changes in the real exchange rate can lead to financial distress in the tradable sectors of the economy.⁽¹⁰⁾

(iii) Bank behaviour — A number of previous empirical studies have found that the credit policies adopted by banks have a direct bearing on the level of subsequent bad debts. In particular, previous authors have shown that rapid credit expansion is often a key factor in the development of problem loans. Banks who seek to expand their loan portfolios too rapidly may inadvertently take on far greater credit risk than they realise which leaves them exposed to high, unexpected losses when these loans go bad. For example, Clair (1992) finds evidence that past credit growth can explain the current level of problem loans, even after controlling for the composition of the bank loan portfolio.

⁽⁹⁾ Recent Bank of England research has developed a measure of the 'concentration' of risk, in the sense that it picks up the extent to which companies with high levels of risk also have high levels of debt. More specifically, Benito and Young (2001) construct so-called 'debt-at-risk' indicators (defined as some measure of default probability multiplied by the outstanding stock of debt) using both aggregate data for the UK corporate sector as a whole and micro firm-specific data. To the extent that the sum of the micro measures of debt-at-risk is greater than the aggregate measure it implies that the amount of debt at risk is concentrated among high-risk companies (ie those with relatively high probabilities of failure).

⁽¹⁰⁾ The impact of changes in the exchange rate on loan defaults is not straightforward — it depends on the reason behind the change. For example, a fall in the exchange rate could reflect an improvement in productivity which might enable borrowers to better service their bank borrowing on the back of stronger economic growth. But equally, the exchange rate depreciation might not deliver any competitiveness gain (ie fall in the real exchange rate) if it merely reflects looser domestic monetary conditions. Moreover, the effect of the exchange rate on borrowers default probabilities will depend on the currency in which the debt is transacted.

In theory, banks can reduce the risks they face by appropriate pricing and screening of transactions, diversifying their asset portfolio, or taking collateral (see Freixas and Rochet (1997)). To the extent that banks anticipate losses on their loan portfolios then these expected losses are likely to be reflected in the margins they earn together with the reward to their shareholders for providing capital to cover potential unexpected losses. Higher provisions (and ultimately losses) may therefore arise from a deliberate policy by banks to engage in riskier lending but charge a risk premium for this business. Previous empirical work provides support for this view. Keeton and Morris (1988) and Sinkey and Greenawalt (1991) find that the banks which charged higher interest rates were those that subsequently experienced higher levels of problem loans. I investigate this issue by including a proxy for each bank's net-interest margin as a regressor. The term is entered in lagged form to capture the idea that the riskiness of past loans is subsequently revealed in higher loan losses.

Credit risks vary significantly across different loan types and, in particular, according to the type of the borrower. If banks do not reflect this variation in their pricing then large-scale provisions are likely to lead to lower profits. Davis (1993) previously investigated the variation of credit risk across loans to different sectors. He found that loans to some sectors — particularly financial institutions (excluding insurance and pension funds), property companies, certain manufacturing industries and construction companies — were associated with much larger provisions. The rate of growth in loans to 'riskier' sectors may therefore provide information on impending problem loans banks may face. Below I consider the share of (sterling) lending to different UK industrial sectors in total (sterling) lending to the UK private and public sectors, focusing in particular on lending to: property companies, construction, non-bank financial institutions and manufacturing firms.

Portfolio diversification can help to limit the overall scale of bank provisions. A less diversified loan portfolio is likely to be associated with higher overall credit risk and therefore higher loan-loss provisions as a proportion of total loans. For example, geographical and industrial sector diversification should reduce overall credit risk. Keeton and Morris (1998) and Solttila and Vihriala (1994) employ different measures of diversification in the loan portfolio - in particular the Herfindahl index of the loan portfolio and the relative share of sector loans in the overall loan portfolio. The size of the bank (typically relative to the sector as a whole) has also been employed in some studies to capture diversification effects under the notion that a large balance sheet facilitates investment in different geographical and business segments to cope with asymmetric shocks (Salas and Saurina (1999)). However, bigger banks may also engage in more risky activities, which can obscure any diversification benefits from greater scale (see Hughes, Mester and Moon (2000)). Consequently in the empirical model below, diversification is proxied solely by a Herfindahl index representing the concentration of the domestic loan portfolio to particular industrial sectors. The hypothesis is that the closer the Herfindahl index is to unity — the more concentrated is the loan portfolio at that bank — the greater the potential for higher overall provisions in the face of greater defaults/delinquencies on bank debt.

Collateral too can reduce credit risk. However, the relationship is not necessarily straightforward. Given the asymmetry of information between banks and their borrowers, the pledging of collateral, as well as providing security against the debt, can reduce any moral hazard facing borrowers. But equally collateral may encourage banks to screen and monitor less effectively which could mean that riskier projects are financed. Berger and Udell (1998) summarise the theoretical and empirical literature in this area and find that collateral is typically associated with risky loans. Below I explore the relationship between

provisions and collateral by considering the ratio of total residential mortgage lending to the total domestic loan book. This clearly can only be a crude proxy for the effect of collateral since it implicitly assumes that all non-mortgage lending is arranged on unsecured terms, which is unlikely to be true.

The effectiveness of banks' monitoring is likely to be an important factor in understanding banks' problem-loan experience. Berger and De Young (1997) found that worsening cost efficiency is associated with increases in problem loans. This could be because inefficient managers are less able to distinguish good quality credits and identify when loans are going bad and take remedial action. It may also be that inefficient banks are more likely to engage in riskier lending, a view which found empirical support in Kwan and Eisenbeis (1997). In the empirical analysis below, two crude proxy variables for firm efficiency are considered: a bank's cost-to-income ratio and the number of staff per domestic branch. However, it is not immediately clear whether these variables should be positively or negatively associated with loan-loss provisions. For example, a high cost-income ratio might imply that a bank is generally inefficient and may be poor at screening credit quality but equally it may mean that the bank maintains high quality but expensive credit evaluation procedures.

(iv) Structural changes in credit markets — The structure of the credit market can affect banks' provisioning experience in a number of ways. In particular, increased competition may encourage banks to take on greater risk to offset any squeeze on margins. But, on the other hand, greater competition may mean that banks are less able to charge higher interest rates in future to firms whose credit quality might be temporarily be low. That is, where banks have some degree of market power in credit markets, they may provide finance to lower-quality firms or those experiencing financial distress, confident that they will be able to charge higher interest rates on loans in the future. Such intertemporal subsidisation would not be possible in a fully competitive market since firms would only pay the market rate of interest. Petersen and Rajan (1995) find some support for this market power hypothesis — they find that a higher proportion of young firms receive financing when the banking market is more concentrated.

Table 5 summarises the specific explanatory variables to be considered in the empirical models together with the expected signs of the coefficients. Given the relatively small sample size the aim is to look for a parsimonious specification so that all of the explanatory variables are unlikely to feature. Moreover, a number of the explanatory variables in Table 5 are likely to be correlated with each other, if not contemporaneously, then possibly through lagged terms. This raises the issue of (multi-) collinearity in the explanatory variables. In the face of multi-collinearity, linear regression models produce inefficient (ie high variance) parameter estimates. In terms of the regression analysis below, where variables are likely to be highly correlated, they are included separately in the regressions to establish their relative statistical significance and explanatory power. Although this is slightly at odds with the generally preferred general-to-specific approach, there are likely to be efficiency gains in terms of the estimated coefficients.

Table 5: Potential explanatory variables and the expected signs of the regression coefficients

Explanatory variable	Expected sign of coefficient	Comment
Aggregate (ie not varying across banks)		
GDP growth	-ve	Backward-looking provisioning suggests that loan impairment will only be recorded when a default event occurs. This suggests that loan-loss provisions will rise when borrowers face sufficient difficulties servicing their debt that banks assess that the debt is unlikely to be repaid.
World output growth	-ve	To capture the international nature of some of the major UK banks' asset portfolios.
Real/nominal interest rates	+ve	× *
Residential house prices	-ve	
Commercial property prices	-ve	
Sterling effective exchange rate	-ve	
Equity prices	-ve	
Corporate capital gearing	+ve	Defined as the stock of corporate debt as a proportion of the corporate sector's capital stock. The latter is measured either at market values or replacement cost.
Corporate income gearing	+ve	Defined as the corporate sector's interest payments as a proportion of net profits.
Household capital gearing	+ve	Defined as the stock of household debt as a proportion of the sum of the stock of household net-financial assets and tangible assets.
Household sector income gearing	+ve	Defined as household interest payments as a proportion of personable disposable income.
Bank-specific		
Overall credit growth	+ve	Refers to loans made by the consolidated banking group. It includes loans made by domestic and overseas banking subsidiaries.
Net interest margins	+ve/-ve	Lagged terms to reflect timing between pricing and realised losses. Uncertain expected sign arises because lower past margins might induce greater risk-taking by banks that could lead to higher losses.
Share of loans and advances to particular risky sectors	+ve	Refers only to domestic sterling lending. It explicitly excludes foreign currency loans and lending by overseas subsidiaries. Loans and advances are reported <u>before</u> provisions.
Herfindahl index of concentration of the loan book	+ve	
Ratio of secured lending to households to total loans	+ve/-ve	Uncertain expected sign reflects different arguments over the impact of collateral on banks' credit risk.
Cost-to-income ratio	+ve/-ve	Measure of cost efficiency.
Number of staff per branch Total assets as a share of total UK banking	+ve/-ve -ve/+ve	Measure of labour efficiency.
sectors' assets		

4. Empirical results

4.1 Preliminary data issues

4.1.1 Provisions ratios – stocks versus flows?

As described above, provisions appear as both a flow and a stock measure in banks' reporting statements. That is, as bad and doubtful debts arise, a new charge (flow) is posted to the profit and loss account and this is added to the stock of provisions (which is typically reported as a contra asset) in the balance sheet. When the debts are actually written off in future periods, the loans are not charged off directly against net income but instead reduce the balance in the stock-of-provisions account. If the bank subsequently recovers part of a loan that it had previously written off, the recovery is added back to the stock of provisions. Formally, the accounting treatment is:

Stock of provisions_t = Stock of $provisions_{t-1}$ + New charge to $P\&L_t - (Write-offs_t - Recoveries_t) + Currency and other adjustments$

Given this accounting identity, the stock measure of provisions may give a misleading picture of current developments in (*ex post*) credit risk. In particular, large write-offs in any one period may mean that the stock of provisions falls even though significant new bad debts have arisen. The new charge against profits is less likely to be affected by such accounting regularities. Moreover, the new charge will pick up loan write-offs that are made immediately following a default event but without prior provisioning. For both reasons I concentrate on the series for the new provisions charge in the empirical analysis below.

4.1.2 Stationarity

Previous authors who have investigated UK bank provisions (eg Davis (1993)) have found that they exhibit non-stationarity (ie they are trended variables). Traditional time series analysis demonstrates the importance of testing for non-stationarity in the data to avoid the problems of spurious regression, and more generally, incorrect inference associated with the presence of unit roots in series. I therefore conduct formal unit root tests on the series for the new provisions charge to loans ratio. Specifically, I employ panel unit root tests, which exploit both cross-section and time-series information in establishing whether series are non-stationary. In doing so, it is possible to augment the power of the normal unit root tests applied to single time series.

Following Im, Pesaran and Shin (1997), Table 6 details the results of the t-bar test procedure for unit roots. The t-bar statistics suggest that the new provisions charge against profits (relative to total loans) is broadly stationary for the sample of UK commercial banks, although the test statistics are sometimes close to the 5% significance critical levels. For the mortgage banks, there is some evidence of a unit root in the ratio of the new provisions charge to total loans. A number of the mortgage banks have recently demutualised and have refocused their businesses away from the domestic property market. This might explain a structural increase in their average loan loss rates over the period. That said, the available information on mortgage banks' provisions is shorter than for the commercial banks in our sample, which is likely to hinder the investigation of possible unit roots.

More generally, the data for the UK commercial banks in our sample span a sufficiently long period that significant structural breaks may have taken place, which may not be picked up by the

statistical tests. Accounting conventions relating to provisioning may not have been constant during the period — before the introduction of the BBA Statement of Recommended Reporting Practice (SORP) few guidelines/rules for accounting for loan impairment were available in the United Kingdom (see Box 2). Past events too could have changed bank behaviour with regard to the amount of and timing of procedures to recognising probable loan losses. The bad debt experience of the 1990s recession may well have made banks more proactive in identifying impaired assets. Similarly, following this loss experience, a number of UK commercial banks scaled back lending to emerging market economies in favour of domestic (in particular mortgages) and international lending to industrial economies. This seems likely to have altered the risk profile of their loan portfolios and could therefore have led to a permanent change in the ratio of provisions to loans. And the changing nature of competition in the UK banking market over the past 20 years or so seems likely to have changed the business mix of the banks under investigation which itself could have led to fundamental changes in the rate of provisions/losses that these banks incur.

It is well known that the power of unit root tests can be low, especially if the series have undergone some form of structural break. Nonetheless in the empirical models below I proceed on the basis that the new charge provisions ratio is stationary and perform regression analysis using the level of the series.

Provisions charge to P&L					
	relative to total loans and				
	advances				
			$C \qquad 1 \qquad \cdot \qquad 1(a)$		
	t-bar statistic – 2		Sample period ^(a)		
	trend (p-values				
	All	Excluding			
	observations	PCD			
		provisions			
Commercial banks					
Raw data	-2.068**	-2.244**	1980–1999 (N=7, T=20)		
	(0.043)	(0.014)			
Demeaned data	-2.526**	-2.454**	1980–1999 (N=7, T=20)		
	(0.002)	(0.003)			
Mortgage banks					
Raw data	-1.856		1987–2000 (N=4, T=13)		
	(0.183)				
Demeaned data	-1.353		1987–2000 (N=4, T=13)		
	(0.474)				
All banks					
Raw data	-1.942**	-1.879	1987–1999 (N=11, T=12)		
	(0.038)	(0.058)			
Demeaned data	-3.941**	-1.531	1987–1999 (N=11, T=12)		
	(0.000)	(0.323)			
Critical values at the 5%	Critical values at the 5% significance level in brackets. ** implies reject null				
hypothesis of a unit root at 5% significance level.					
(a) The t-bar statistic is	based on a balance	ed panel. The	prefore, the different samples		
are chosen so that the observations on each of the banks are available for all time					
periods.					

Table 6:	Unit root tests for	panel data — t-bar	· test procedure (Ho	: There exists a unit root)
		1		,

4.2 Main findings

4.2.1 Static pooled regression model

Tables 7 and 8 present the results from the static pooled regression models.⁽¹¹⁾ Given the likely differences in their businesses, separate regressions were undertaken for commercial and mortgage banks. Broadly speaking, the reported regression specifications reflect a strategy of testing down from general to specific, eliminating insignificant explanatory variables at successive stages, to arrive at the specifications reported in the table. Two lags were initially applied to each of the explanatory variables and in testing down from this general model, insignificant terms were removed.⁽¹²⁾ In terms of the regression diagnostics, there was some evidence of both heteroscedasticity and serial correlation in ordinary least squares (OLS) equation residuals, as might be expected given the panel nature of the dataset. Consequently a (Prais-Winsten) Generalised Least Squares (GLS) estimator with first-order serially correlated errors was employed.

Preliminary estimations (not reported) revealed non-normal errors the presence of which hinders correct inference in hypothesis testing. Closer inspection of the residuals suggested that observations in the late 1980s/early 1990s (particularly for Lloyds, Midland and Standard Chartered) were particular outliers. Since this is a period of particular interest — it was a recession period for the UK economy — there was little merit in excluding these observations altogether. Moreover, these are the banks that made large loan-loss provisions against PCD over this period. Table 7 therefore concentrates on the results of regressions where the PCD provisions are excluded for the UK commercial banks. The residuals in these equations appeared to be normal.

The main points to emerge from the regressions are:

UK commercial banks

As expected, GDP growth shows a negative relationship with the provisions — lower GDP growth is associated with a higher provisions charge ratio. The coefficient estimates, suggests that for each 1 percentage point decrease in GDP growth, the new provisions charge ratio increases by about 8%. Alternative activity measures such as the unemployment rate and the output gap were not found to be significant.

World GDP growth also exerts a negative influence on bank provisioning — ie slower world activity is associated with higher bank provisions. This illustrates the international loan exposure of a number of the UK commercial banks. The regressions suggest that the effect on UK banks'

⁽¹¹⁾ In the regressions, the logit transformation was applied to the new provisions charge odds ratio — ie $\ln(y/(1-y))$ where y is the ratio of the new provisions charge to loans. This transformation ensures that the dependent variable can be mapped to the real line (ie take a value between $-\infty$ and $+\infty$); the ratio of provisions to total loans is bounded by 0 and 1. It does, however, mean that interpretation of the coefficients can be problematic. Formally the regression coefficient β_k represents the change in the logarithm of the odds associated with a unit change in the value of the *k*th explanatory variable, x_k . Thus, e^{β_k} is the ratio of the odds associated with a change in one unit of x_k . In our model, the provisions ratio is usually a small number — less than 0.1 — and so the coefficient β_k approximates to the percentage change in the provisions ratio for a unit change in x_k .

⁽¹²⁾ The chosen lag length is arbitrary. Given that the data are of annual frequency, most of the factors affecting problem loans seem likely to feed through within a relatively short window. From a statistical perspective too, the estimation sample is not large, and so increasing the number of lags significantly reduces the number of degrees of freedom.

provisions of slower world activity is slightly larger in scale compared with slower domestic activity. However, a Wald test on the equality of these coefficients on UK GDP growth and world GDP growth could not be rejected at the 1% significance level.

	(1)	(2)	(3)
	Ln[xprF/(1-	ln[xprF/(1-xprF)]	ln[xprF/(1-xprF)]
	xprF)]		
gdp_g	-0.073***	-0.067**	-0.077***
	(0.005)	(0.018)	(0.004)
L1.gdp_g	-0.003		
	(0.901)		
wgdp_g	-0.092*	-0.095*	-0.078*
	(0.051)	(0.050)	(0.094)
L1.wgdp_g	0.000		
	(0.993)		
rr	0.032		
	(0.184)		
L1.rr	0.091***	0.096***	0.097***
	(0.000)	(0.000)	(0.000)
L3.m4l_12g	0.034***	0.039***	0.040***
	(0.003)	(0.000)	(0.000)
propsh	-0.029		
	(0.351)		
L1.propsh	0.060*	0.043**	0.039**
	(0.063)	(0.036)	(0.025)
herf	6.876***	3.416***	3.139***
	(0.001)	(0.001)	(0.000)
L1.herf	-4.785**	. ,	
	(0.035)		
cyr	-0.007		
-	(0.268)		
L1.cyr	0.011*	0.009*	
	(0.078)	(0.052)	
L1.nim	0.067		
	(0.497)		
Nat81	-1.194***	-1.187***	-1.195***
	(0.002)	(0.002)	(0.000)
Nat87	-1.060***	-1.028***	-0.978***
	(0.008)	(0.007)	(0.001)
Constant	-6.481***	-6.822***	-6.269***
	(0.000)	(0.000)	(0.000)
Observations	127	128	146
Number of id	7	7	7
R-squared	0.807	0.777	0.769
Wald test of joint coeff sig F=	165.220	123.625	133.155
prob>F	0.000	0.000	0.000
H0: Normal residuals Z=	0.802	1.547	1.387
Prob > z	0.211	0.061	0.083

Table 7: Static pooled regression: UK commercial banks (1978–2000)
Dependent variable : (Provisions charge to P&L log-odds ratio $-\ln(xprF1_{it}/(1-xprF1_{it}))$

p values in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Prais-Winsten regression with first-order serially residuals and correlated panel corrected standard errors (PCSEs).

Nominal interest rates were positively related to provisions and retail price inflation appeared to exert a negative influence on the provision ratio. However, reformulating the specification to include a term for (*ex post*) real interest rates suggested that a percentage point increase in (*ex post*) real interest rates increased the bank provisions ratio by around 10%.

Terms to capture capital and income gearing in the household and corporate sectors were not generally significant in the regression specifications — where they were significant, other terms for GDP growth and real interest rates became insignificant.⁽¹³⁾ Similarly, terms in the (log) levels of asset prices — exchange rates, equity prices and property prices — were not found to be significant in any of the regressions.

In some regressions, the coefficient on the lagged growth rate of *individual* banks' total loans was significantly negative although it was very small. This was true for varying lag lengths and does not support the notion that rapid loan growth necessarily brings with it potential bad debt problems. A similar result was also found in the study by Cavallo and Majnoni (2001). However, the demand for credit seems likely to fall when aggregate demand in the economy is weakening. The negative coefficient may therefore be picking up this negative demand effect. This term was therefore dropped from the regressions and replaced with lagged *aggregate* bank and building society sterling lending growth to the UK private sector (M4 lending). The aggregate lending growth term was significant in the regressions, suggesting that banks who grow their loan books are more likely to face higher future loss rates if other banks' loan portfolios are also growing. That is, in an environment of rapid domestic lending growth, banks may find that the average quality of their borrowers falls and this subsequently leads to significantly higher credit losses.

Faster growth to certain traditionally 'riskier' sectors would also seem to translate into larger loss rates. In particular, an increase in the share of bank lending to commercial property companies (which will reflect faster growth to this sector in previous periods) signals increased banks' provision ratios. Lending shares to other 'risky' sectors such as manufacturing, agriculture and personal unsecured borrowing were not found to significantly affect banks' provisions ratios. Similarly, the share of domestic lending secured against residential property, a proxy for the role of collateral in ameliorating loan losses, was not found to be significant.

Among the other bank-specific variables, greater concentration in the loan portfolio was associated with a higher provisions-to-loans ratio. This indicates that increased diversification, at least in the domestic loan portfolio, is important in limiting overall loan losses. However, other potential influences such as (lagged) net-interest margins, and the share of a banks' assets in total UK banking sector assets (a proxy for market power) were not found to be statistically significant, at least across the different regression specifications investigated. Similarly, a bank's overall share in the domestic credit market, as a proxy for market power and the influence of competition, was not influential.

Cost efficiency, as proxied by the cost-to-income ratio, was statistically significant. But the coefficient was very small indicating that operating costs themselves are unlikely to exert an economically significant effect on bank provisions.

UK mortgage banks

For mortgage banks, given the high proportion of their loans that relate to the domestic residential housing market, a number of the explanatory variables were not likely to be relevant — in particular world GDP growth, and domestic lending to commercial property companies — and these terms were therefore dropped. Nonetheless, a number of terms relevant for commercial banks were also significant for mortgage banks.

⁽¹³⁾ Experimental regressions including terms related to debt-at-risk were also undertaken. But the significance of these terms was sensitive to the definition of real interest rates.

GDP growth was negatively associated with mortgage banks' provision charges. In fact, the effect of economic activity is larger then for commercial banks. This seems intuitive given the concentration of mortgage bank lending to domestic borrowers.

Real interest rates also positively influence the new provisions charge ratio, although the effect is sensitive to the definition of the real interest rates. Calculations of real interest rates using retail prices were not found to be significant. But short-term interest rates deflated by house price inflation were positively associated with loan-loss provisions. This suggests that mortgagors may be more likely to default if higher nominal interest rates are not accompanied by house price growth of a similar magnitude, perhaps reflecting their inability to re-finance their debt by extracting equity in their property.

For mortgage banks, loans are typically highly concentrated in secured residential property lending. The Herfindahl index of loan concentration is therefore highly correlated with the share of (residential) mortgage lending in domestic loan portfolio. In turn, the regressions suggested that the share of mortgage loans in total loans was *negatively* associated with the new charge provisions ratio. This would seem to suggest that collateral can indeed ameliorate realised losses for the mortgage banks.

	(1)	(2)
	ln[prF/(1-prF)]	ln[prF/(1-prF)]
gdp_g	-0.151	-0.131*
	(0.175)	(0.059)
L1.rr	0.064	< <i>, , ,</i>
	(0.600)	
L3.m4l 12g	0.017	
_ 0	(0.635)	
secsh	-0.113***	-0.100***
	(0.000)	(0.000)
cyr	-0.085***	-0.066***
	(0.000)	(0.000)
L1.nim	1.650***	1.132***
	(0.001)	(0.000)
L1.rr_hse		0.067***
		(0.000)
Constant	4.287*	3.493**
	(0.060)	(0.021)
Observations	52	52
Number of id	4	4
R-squared	0.794	0.808
Wald test of joint coeff sig F=	35.955	110.028
prob>F	0.000	0.000
H0: Normal residuals Z=	0.386	-0.274
Prob >z	0.350	0.608

Table 8: Static pooled regression: UK mortgage banks (1986–2000) Dependent variable: (Provisions charge to P&L log-odds ratio – ln(prF_{it}/(1- prF_{it}))

p values in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Prais-Winsten regression correlated panels corrected standard errors (PCSEs).

Unlike for commercial banks, higher lagged interest margins were an important positive influence on mortgage banks' provisions. This seems reasonable since mortgage banks have switched to higher margin, higher risk loan business over recent years.⁽¹⁴⁾

4.2.2 Dynamic regression model

Table 9 presents the regression results for a GMM estimated dynamic panel model. Given the limited number of observations for mortgage banks, I concentrate solely on the commercial bank sample. The regressions include at most two lags of the dependent variable. Tests for higher than second-order autocorrelation in the residuals suggested that the inclusion of one lag on the dependent variable was sufficient to account for the serial correlation in the residuals.

(1)	(2)
	ln[xprF/(1-xprF)]
	0.264***
	(0.001)
	0.031***
	(0.002)
	3.373**
	(0.013)
	(0.015)
· · · ·	-0.076***
	(0.002)
. ,	-0.092***
	(0.000)
	0.088***
	(0.000)
. ,	0.031***
	(0.002)
	-1.488***
	(0.000)
	-1.295***
	(0.000)
	-0.005
	(0.428)
	137
	7
,	19739.679
	0.000
	-2.177
	0.029
	-0.596
	0.551
	(1) n[xprF/(1-xprF)] 0.247*** (0.003) 0.027*** (0.005) 3.000*** (0.005) 3.000*** (0.002) 0.008 (0.177) 0.119* (0.095) -0.072*** (0.009) -0.096*** (0.003) 0.080*** (0.003) 0.034*** (0.003) 0.034*** (0.002) -1.488*** (0.000) -1.239*** (0.000) -1.239*** (0.000) 0.012* (0.055) 120 7 22643.720 0.000 -2.179 0.029 0.061 0.951

Table 9: Dynamic pooled regression: UK commercial banks (1978–2000) Dependent variable: (Provisions charge to P&L log-odds ratio – ln(xprF1_{it}/(1- xprF1_{it}))

Robust p values in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Arellano-Bond (first-differenced) GMM estimator. Bank-specific variables were treated as pre-determined in the associated instrument matrix.

⁽¹⁴⁾ However, this result underlies how the potential non-stationarity in mortgage banks' provisions ratios should be borne in mind in interpreting the regressions.

In all of the regressions, the lagged dependent variable was highly significant with a coefficient of typically around 0.25. Virtually all of the terms that were significant in the static model also remained significant in the dynamic specification with similar-sized coefficients. In particular, GDP growth, world GDP growth, real interest rates and lagged aggregate lending growth were all significant. And the bank-specific variables describing the share of domestic lending to commercial property companies and the degree of concentration in the domestic loan portfolio remained significant with similar-sized coefficients in the dynamic model.

The cost-efficiency term was not significant in the dynamic regressions. Similarly, although the coefficient on the interest margins term suggested that there may be some positive influence of past margins on new loan-loss provision charges, the statistical significance of such an effect was marginal.

5. Robustness of the model specifications

To assess the robustness of the various model specifications I have undertaken three types of investigation: (i) the models were estimated using a subset of banks to investigate further the panel structure of the dataset; (ii) formal tests of the appropriateness of pooling the data on provisioning across banks were undertaken; and (iii) stability checks on the model were made. Given that the available observations were much greater for the commercial bank sample, I again concentrate on the commercial banks in this section.

5.1 Different bank samples

Although the commercial banks in the sample share the characteristic that they are all UK-owned, given their different business profiles, some of the banks may be more alike. For example, Standard Chartered bank conducts most of its loan business outside of the United Kingdom and therefore its provisions are more likely be influenced by world factors than the other banks. To investigate this, I re-estimated the models on restricted samples where each time one of the commercial banks was excluded. The results suggested that most of the macroeconomic and bank-specific variables remained significant in the reduced-sample pooled regressions. This would seem to indicate that the UK commercial banks' loss experience can indeed be related to some common factors, even though their individual businesses obviously differ.

5.2 Can the UK commercial banks' loan-loss provisions data really be pooled?

A key assumption of the regression specifications is that the effects of the various explanatory factors on loan-loss provisions are the same across banks. That is, the estimated (slope) coefficients are the same for all banks in our separate mortgage and commercial bank samples. This hypothesis can be empirically tested using a simple linear restriction Wald test. Specifically, I introduce step and interactive dummies into the pooled regression model to allow for individual bank specific effects and test the significance of these dummy variable terms. Given the number of estimated coefficients, the available degrees of freedom (number of observations less estimated parameters) do not permit a fully interacted dummy variable model to be estimated. But it is potentially useful to test whether any bank-specific effects can be detected in the intercept term or whether some of the slope coefficients also differ across banks. For example, for the static model, in order to investigate bank specific intercept terms versus bank specific coefficients on the GDP growth term I estimate:

$$\ln(xprF_{it} / (1 - xprF_{it}) = \alpha + \beta_1 gdp _ g_t + \beta_2 wgdp _ g_t + \beta_3 rr_{t-1} + \beta_4 M 4L _ 12g_{it-3} + \beta_5 propsh_{it-1} + \beta_6 herf_{it} + d_2 + d_3 + d_4 + d_5 + d_6 + d_7 + d_2 * gdp _ g_t + d_3 * gdp _ g_t + d_4 * gdp _ g_t + d_5 * gdp _ g_t + d_6 * gdp _ g_t + d_7 * gdp _ g_t + u_{it}$$

where d_i are step dummies corresponding to each of the banks in the sample.⁽¹⁵⁾ I then test separately for the joint significance of the step and interactive dummies in the regression using a Wald test.⁽¹⁶⁾

$ \begin{array}{c c c c c c c c c c c c c c c c c c c $		UK commercial banks (excluding PCD provisions)					
included in regression(Column (3) of Table 7)(Column (2) of Table 9)(Column (3) of Table 7)(Column (2) of Table 9)(Under uit -N(0,Ω)Intercept dummies (Ho: d_=0 for all i)Wald Test on Interactive dummies (Ho: d_i*Regressor=0)(Ho: d_=0 for all i)Wald Test on Interactive dummies (Ho: d_i*Regressor=0)Wald Test on Interactive dummies (Ho: d_i*Regressor=0)di, i=2,,7chi2(6) = 5.43 Prob > chi2 = 0.4899chi2(6) = 7.60 Prob > chi2 = 0.2693chi2(6) = 10.05 Prob > chi2 = 0.1227di, i=2,,7chi2(6) = 9.25 Prob > chi2 = 0.1598chi2(6) = 10.92 Prob > chi2 = 0.0910chi2(6) = 3.88 Prob > chi2 = 0.6929di, i=2,,7chi2(6) = 9.31 Prob > chi2 = 0.1566chi2(6) = 16.32 Prob > chi2 = 0.0011chi2(6) = 3.97 Prob > chi2 = 0.6805di, i=2,,7chi2(6) = 23.60 Prob > chi2 = 0.0001chi2(6) = 18.35 Prob > chi2 = 0.0001Prob > chi2 = 0.0054di, i=2,,7chi2(6) = 3.25 Prob > chi2 = 0.1382chi2(6) = 10.44 Prob > chi2 = 0.1074Prob > chi2 = 0.1074di, i=2,,7chi2(6) = 11.34 Prob > chi2 = 0.0775chi2(6) = 9.31 Prob > chi2 = 0.1382chi2(6) = 12.69 Prob > chi2 = 0.0482(a) The dynamic model was estimated without imposing robust standard errors. This is because the procedure to select the appropriate instrument set became unstable. However, it does mean that the standard errors on the coefficients may be biased and therefore the results of hypothesis testing on the dynamic model are less reliable.(b) The dynamic model is estimated in first differences and so any bank-specific effect in the level of	Dummies	Static	model	Dynamic model ^{(a), (b)}			
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Table 10:	Hypothesis	tests on	'poolability'	of regression
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The results of this test procedure are given in Table 10. Most of the Wald significance tests cannot reject the hypothesis that the shift and interactive dummy terms are zero implying that there is evidence that the intercept and at least some of the slope coefficients are likely to be

⁽¹⁵⁾ There are seven banks in the UK commercial bank sample, but only six dummies are included in the equation to avoid the 'dummy variable trap'.

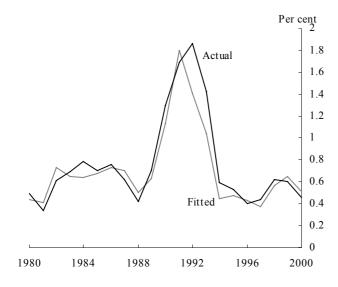
⁽¹⁶⁾ Since the model is not fully interacted, inference is conditional on the regression model that includes the dummy variables. This is not the same as the fully unconstrained model underlying pooled regression model considered in tables. This means that I cannot isolate completely the bank-specific effects that are ignored in the pooled model. Nonetheless, this procedure should provide an idea where the most significant differences in the estimated coefficients across banks' experience may reveal themselves.

common across banks. In turn, this would suggest that pooling the data for the commercial bank sample is appropriate.

5.3 Stability checks

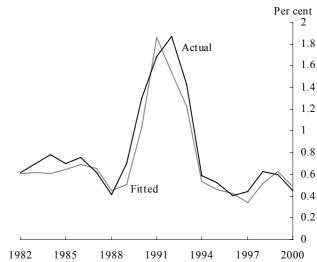
Charts 10 and 11 show respectively the actual and model predictions for the static and dynamic models for new bad-debt charges (excluding the PCD provisions) averaged across the seven UK commercial banks — charts for the individual banks are shown in Appendix 2. The fitted values are based on the 'static' pooled GLS model in Table 7 (column (3)) and the dynamic GMM model in Table 9 (column (2)).⁽¹⁷⁾ Broadly speaking the models track the average new provisions charge to loans ratio reasonably well — both the static and dynamic models are able to pick up the key turning points. However, as shown in Appendix 2, the prediction intervals are quite wide for both models — for example, the 95% confidence level suggests that the average commercial banks' new provisions could reasonably be expected to vary between around 1% and 4% of loans for most banks.

Chart 10: New provisions charge-to-loans ratio (average UK commercial banks) actual and fitted values for static model^(a)



(a) The fitted values are constructed by first inverting the logit transformation and then averaging across banks.





(a) The fitted values are constructed by first inverting the logit transformation and then averaging across banks.

(b) Since the dynamic model is estimated in first differences, in order to derive predictions for the level of the new provisions charge ratio, fitted and actual values were assumed to be equal in 1982.

Table 11 presents the results of Wald tests that consider how much the model estimated over a subsample differs from the model over the whole sample period. That is, are the estimated coefficients the same before and after a particular possible breakpoint period? In order to ensure sufficient observations for estimation, I investigate potential breakpoints at points near the middle

⁽¹⁷⁾ The fitted values for the static model are based on the in-sample values for the right-hand side regressors but they ignore the autocorrelation in the disturbance term.

of the sample period — specifically 1990, 1992 and 1994. Separate tests were undertaken for the static pooled GLS and the dynamic GMM models.

	Potential breakpoint years:			
Model	1988	1990	1992	1994
Static pooled (UK commercial banks)	chi2(7) = 11.35	Chi2(7) = 25.43	chi2(7) = 19.35	chi2(7) = 7.61
H0: intercept and slope coefficients are the same when model is estimated over the full sample and the subsample	Prob > chi2 = 0.1240	Prob > chi2 = 0.0006	Prob > chi2 = 0.0072	Prob > chi2 = 0.3686
Dynamic pooled (UK commercial banks) H0: intercept and slope coefficients are the same when model is estimated over the full sample and the subsample	chi2(7) = 10.95 Prob > chi2 = 0.1407	Chi2(7) = 14.02 Prob > chi2 = 0.0509	chi2(7) = 10.80 Prob > chi2 = 0.1474	chi2(6) = 11.94 Prob > chi2 = 0.0632
Bold entries imply that there is evidence, at the 5% significance level, that the coefficients are common across subsamples.				

Table 11: Wald test for possible breakpoints

On the whole, the results suggest that the model parameters are likely to be stable even when the model is estimated over subsamples. The UK recession period of the early 1990s could be a potential breakpoint in the model but either side of this period the coefficient estimates still appear to be stable.

6. Concluding remarks

Provisions for bad and doubtful debts typically account for a large part of the volatility in United Kingdom bank profitability and can potentially lead to significant fluctuations in bank capital. Understanding what factors drive provisions may therefore be important in assessing bank fragility. The empirical models outlined in this paper support the view that the economic cycle and changes in asset prices are important influences on bank provisioning — presumably because they capture changes in the ability of borrowers to repay their bank debt. Specifically, for commercial banks low GDP growth (both in the United Kingdom and overseas), high (*ex post*) real interest rates and faster lagged growth in aggregate lending are associated with increased provisions; for mortgage banks the relevant macroeconomic drivers would seem to be domestic economic activity and domestic interest rates deflated by house price inflation.

As well as these macroeconomic factors, bank behaviour also plays a role. In particular, the composition of the loan portfolio is important. Increased lending to riskier sectors, in particular commercial property companies, is associated with greater commercial bank provisions. More generally, greater industrial concentration of commercial banks' loan portfolios can lead to increased bad-debt charges. This is not the case for mortgage banks. A high proportion of their commercial assets are secured against residential property and this collateral seems to reduce loan-loss provision charges.

Such formal models can be helpful in attempting to quantify the impact of external factors on bank stability. But there is an important caveat. Past experience may not always be a good guide to the future. In particular, the change in monetary policy regime may have permanently affected the macroeconomic environment in which banks operate. Together with improvements in risk management practices this may mean that banks are now able to cope better with credit risk in their loan portfolios.

Appendix 1: Data definitions and sources

(i)	prF _{it} = New charge of total loan-loss provisions/(Stock of loans and advances to customers + Stock of total loan-loss provisions) Source: Banks' annual reports. Consolidated balance sheet entries
(ii)	xprF _{it} = New charge of total loan-loss provisions (excluding PCD provisions)/(Stock of loans and advances to customers + Stock of total loan-loss provisions (excluding PCD provisions)) Source: Banks' annual reports. Consolidated balance sheet entries and Bank calculations
(iii)	gdp_g _t = UK real GDP at constant factor cost (1995 prices) Source: ONS, code: YBHH
(iv)	pgdp _t = GDP deflator at market prices Source: ONS, code:YBGB
(v)	wgdp_g = World GDP growth Source: IMF <i>World Economic Outlook</i>
(vi)	base = London clearing banks' base rate Source: ONS, code: AMIH
(vii)	IB_3 _t =London three-month interbank offer rate Source: ONS, code: AMIJ
(viii)	$rr_t = ex \ post \ real \ interest \ rate \ calculated \ as the annual average \ of \ (1+BASE \ in \ quarter \ i) divided \ by \ (1+four-quarter \ percentage \ change \ in \ pgdp \ in \ quarter \ i+1)$
(ix)	$rr_hse_t = IB_3_t$ less annual percentage change in DTLR house price index
(x)	$m4l_{12g} = Twelve-month growth rate in aggregate M4 lending$
(xi)	$loan_{it}$ = Loans and advances to customers Source: Banks' annual accounts. Consolidated balance sheet entries. This will cover the exposures of both <u>domestic</u> and <u>overseas</u> entities in the banking group.
(xii)	nim _{it} = Net interest income/Total assets Source: Banks' annual accounts. Consolidated P&L and balance sheet entries
(xiii)	cyr _{it} = 'implied' cost-to-income ratio Source: Banks' annual accounts. Consolidated P&L entries
	Where possible, cost-income ratios reported by banks are used. But where these are not reported, the ratio has been inferred from applying the proportionate changes in:
	$(II + NII - \Pi_{prov})/(II + NII)$

where II = Interest income

NII = Non-interest income \prod_{prov} = Profit before provisions

(xiv) herf_{it} = Herfindahl index of concentration of the (sterling) loans and advances to UK private and public sector. Formally, the index is constructed as:

$$herf_{it} = \sum_{j} s_{j}$$

where s_j is the share of loans to the jth sector in total (sterling) loans and advances to the UK private and public sector.

The sectors chosen relate to the 2-digit UK SIC classification. They are: Agriculture, Forestry and Fishing, Energy and Water Supply, Manufacturing, Construction, Garages and Distribution, Hotels and Catering, Transport and Communication, Commercial Property, Financial Intermediation, Household Bridging finance, Loans Secured on Residential Property, and Other loans and advances to individuals. These sectors typically account for around 90% of UK banks' (sterling) loans and advances to the UK private and public sectors. But a property of the Herfindahl index is that it is not significantly biased if one assumes that all missing market shares are equal to one another. Hence, I assume that the remaining 10% (approximate) of loans are equally spread over the remaining specified industries.

Source: Bank of England. Unconsolidated data on banks' assets. Data are derived for each banking group by summing the available data for each individual authorised entity within that group. The series reflect acquisitions and disposals of subsidiaries that are authorised deposit-takers.

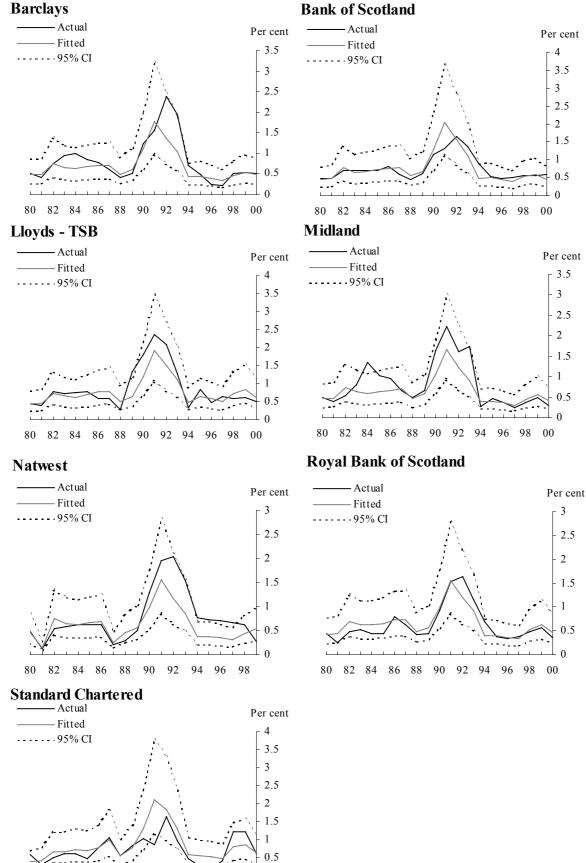
- (xv) propsh_{it} = sterling loans and advances to property companies as a percentage of total UK private and public sector loans and advances by bank i.
- (xvi) secsh_{it} = sterling loans and advances secured as residential property as a percentage of total UK private and public sector loans and advances by bank i.

Source: Bank of England. Unconsolidated data on banks' assets. Data are derived for each banking group by summing the available data for each individual authorised entity within that group. The series reflect acquisitions and disposals of subsidiaries that are authorised deposit-takers.

For the mortgage banks, data for the composition of their loan portfolio prior to their demutualisation is based on consolidated balance sheet information reprinted in the *Building Societies Association Annual Year Book*. Details relate solely to the share of loans secured on residential property in total loans and advances to customers. But for all four banks, this accounted for over 90% of loans and advances in the years prior to conversion to bank status.

(xvii) Nat81, Nat87 are shift dummies corresponding to observations for NatWest bank for the years 1981 and 1987.

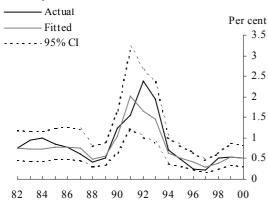
Appendix 2 Static model predictions – UK commercial banks (exc. PCD provisions)



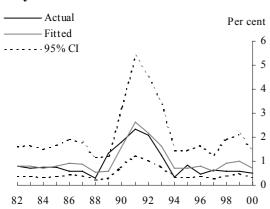
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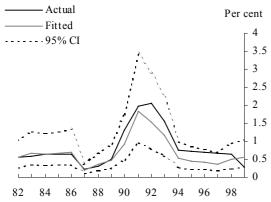
Dynamic model predictions — UK commercial banks (exc. PCD provisions) Barclays Bank of Scotland



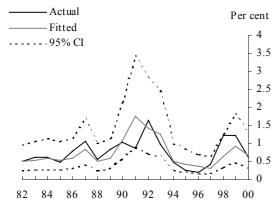


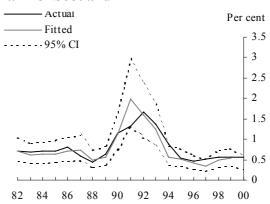




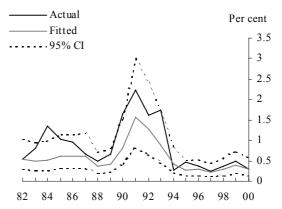


Standard Chartered

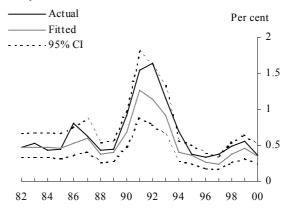




Midland



Royal Bank of Scotland



Box 1: The impact of the early 1980s emerging market debt crisis on the major UK commercial banks' provisioning

International lending to developing countries rose sharply in the 1970s. By the end of the decade, commercial banks — including the major UK ones — had taken over from governments and multi-lateral institutions as the largest group of creditors to the highly indebted countries. They held around 70% of their debt compared with around 30% in 1970s.⁽¹⁾ The sharp tightening of US monetary policy in the late 1970s and the ensuing US recession depressed commodity prices and slowed growth in world trade. Against that background, Mexico suspended payments of interest and principal in 1982. Similar actions by other countries in Latin America (and elsewhere), followed.

The impact of the crisis was initially contained by official intervention. The International Monetary Fund (IMF) provided funds and encouraged creditors to provide new funds and reschedule debts. Moreover, following the so-called Baker initiative,⁽²⁾ a number of market-based financial instruments were developed which reduced banks' debt exposure. In particular, debt-for-equity swaps, whereby the creditor received local currency in settlement of the debt and re-invested in claims on real assets of the debtor country, were introduced. Estimates suggest that, by 1989, the 15 countries named in the Baker initiative had reduced their bank debt by around 13% through such re-financing.

However, over this period, interest arrears continued to increase. Further, Brazil announced a moratorium on interest payments in February 1987. Subsequently, a number of banks made substantial provisions against this debt.⁽³⁾ Among the major UK commercial banks, Barclays, Lloyds, Midland, NatWest and Standard Chartered all made large bad-debt charges against profits in 1987.

In March 1989, Nicholas Brady, the US Treasury Secretary, announced new proposals to deal with the debt crisis. The Brady initiative shifted the policy emphasis towards debt and debt-service reduction, supported by official resources from government and multilateral institutions. A number of financial instruments (so-called Brady bonds) were created which enabled banks to 'sell-off' some of their developing country problem loans to developing countries. However, in the first negotiations to take place within the Brady framework, between Mexico and the commercial banks, it became clear that available official resources would be insufficient to support the scale of debt reduction originally envisaged. Consequently in 1989 a number of banks, including the major UK commercial banks, raised provisions still further.

Table A shows the stock provisions made by the UK commercial banks against problem-country debt (PCD). All of the UK commercial banks held provisions amounting to at least 50% of their exposures to these countries during the period 1987–92 and in some cases such provisions were nearer 80% of the bank's exposures. Some of these provisions were later removed as the some of the exposures were sold, and some provisions were released as the asset quality improved. But a significant part of these provisions were subsequently written-off against PCD.

For most of the major UK commercial banks the process of unwinding/writing-off of the PCD provisions was largely complete by the mid-1990s. Chart A shows the stock of provisions excluding those related to PCD relative to total loans for each of the major UK banks. A comparison with Chart 1 in the main text suggests that the PCD provisions have a significant effect on the profile of the provisions ratio of the UK commercial banks. In particular, the scale of the provisions is significantly reduced — over the period 1980–2000, the average ratio for all seven commercial banks is 2.2% excluding the PCD provisions compared with 2.6% for all provisions.

⁽¹⁾ Figures quoted from *Midland Group Financial Review* (1989).

⁽²⁾ In 1985, James Baker was the US Treasury Secretary. He proposed that growth-oriented reforms should be adopted, supported by increased lending from both official institutions and banks, to address the debt crisis. The hope was that developing countries would, over time, grow out of their debt burden.

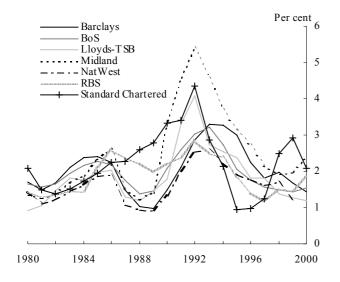
⁽³⁾ The trigger event was the decision in May 1987 by the US bank Citicorp to significantly increase its provisions against developing country loans.

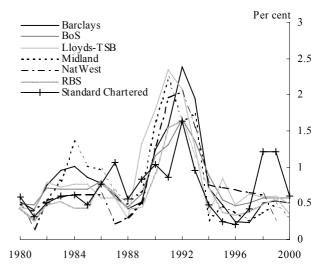
Stock of provisions against PCD	1987	1988	1989	1990	1991	1992
£mn (Per cent of PCD exposure in brackets)						
Barclays	825	854	1580	869	603	662
	(29.1)	(31.4)	(61.8)	(68)	(45.7)	(45)
BoS	43.6	42.9	41.8	30.0	29.9	38
	(33)	(38)	(75)	(78)	(77)	(81)
Lloyds	1333	1274	3050	2807	2805	2124
	(33.9)	(33.6)	(71.9)	(72.7)	(83)	(77)
Midland	1206	1363	2173	1224	1126	820
	(29.2)	(32.6)	(50.2)	(66.9)	(63.2)	(47.9)
NatWest	830	861	1237	348	67	
		(35)	(75)	(62.1)	(26)	
RBS	105	108.2	186.2	31.1		
	(32.3)	(35.9)	(74.8)	(78.7)		
Standard Chartered	617.9	620.3	859.8	577.3	473.2	523
	(25)	(27.1)	(42.8)		(39.1)	(39.1)

Table A: Evolution of major UK commercial banks' loan-loss provisions against PCD

Chart A: Stock of provisions-to-loans ratio (excluding PCD provisions) — UK commercial banks

Chart B: New provisions charge-to-loans ratio (excluding PCD provisions) — UK commercial banks





Box 2: UK accounting rules for provisions

The Companies Act (1985) stated that assets should be valued in the balance sheet at the lower of cost and net realisable value. However, beyond this legislation, there are few formal rules governing provisioning by UK banks. The British Banking Association's (BBA) Statement of Recommended Practice (SORP), introduced in 1992, provides a recommended accounting treatment for loans and provisions for banks but the statement is <u>not mandatory</u> in the way are the Companies Act or the Accounting Standard Board (ASB) rules. The BBA's SORP suggests that:

- Provisions are for impairment at the balance sheet date. They should be made only when the position has deteriorated to an extent not foreseen when the advance was made (ie above the normal credit risk originally priced into the loan). There is no specific trigger it is often a default event but provisions should be made whenever information suggests impairment.
- Specific provisions should be the bank's estimate of the amount needed to reduce the balance sheet value of the loans to the expected, ultimate realisable amount.
- General provisions should be for advances already impaired but not yet identified. The assessment for general provisioning is 'inevitably subjective' but it should take into account past experience and current economic conditions.
- Country risk should be separately disclosed.
- Interest is normally accrued on loans provided that its receipt is not in doubt. No specific guidance is given as to when the receipt of interest becomes doubtful.
- Accrued interest which is not yet due and interest which is due but has not been paid should be excluded from the P&L account when it is identified as doubtful and credited to an interest suspense account. (Previously interest was accrued even when the loan was in doubt, and an appropriate provision was raised. Interest was accrued in this way until recovery was unlikely.)

Although most UK banks are likely to have implemented these BBA guidelines to some extent, there is some flexibility in how they are applied. For example, despite the SORP stating that general provisions should relate only to 'impairment already existing in a loan portfolio', some banks have established forward-looking provisioning policies that attempt to cover some expected losses over the life of a loan. That said, in practice, general provisions are only a relatively small part of total provisions, probably, at least in part, a reflection of the fact that general provisions are not tax-deductible and that the Basel Capital Accord (1988) limited the inclusion of general provisions in regulatory capital to 1.25% of risk-weighted assets.

To the extent that UK banks may well have followed practices overseas, the rules applied in the United States may be particularly relevant since a number of the major UK banks are registered with the SEC. In the United States, the 1975 SFAS 5, 'Accounting for Contingencies' suggests that losses must be probable — ie provisions should relate to an asset that is already impaired. Specifically, it states that losses should be registered when: 'information available at the year-end suggests impairment; and the loss can be reasonably estimated.'

In terms of timing, the identification of the point at which a loan is considered non-performing and therefore may require a provision to be created is very much a matter of judgment. Some banks may use the fact that interest is overdue by some specified period as the convenient starting point. But this is not always true — signs of non-performing loans do not automatically mean that the loan should be considered doubtful and requiring a provision. Neither the BBA SORP nor the US standards specify how a creditor should determine if the collectability of a loan has become doubtful.

Overall, the UK accounting and regulatory framework concerning provisioning leave a good deal to banks' judgment. The UK regulator, the Financial Services Authority, does though require banks to give a statement on their provisioning practices, which often includes information on how they categorise loans.

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