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Abstract

We demonstrate how the introduction of liability-side feedbacks affects the properties of a quantitative model of systemic risk. The model is known as RAMSI and is still in its development phase. It is based on detailed balance sheets for UK banks and encompasses macro-credit risk, interest and non-interest income risk, network interactions, and feedback effects. Funding liquidity risk is introduced by allowing for rating downgrades and incorporating a simple framework in which concerns over solvency, funding profiles and confidence may trigger the outright closure of funding markets to particular institutions. In presenting results, we focus on aggregate distributions and analysis of a scenario in which large losses at some banks can be exacerbated by liability-side feedbacks, leading to system-wide instability.

Key words: Systemic risk, financial stability models, funding liquidity risk, contagion.

JEL classification: G01, G21, G32.

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Summary

The global financial crisis of 2007-09 has illustrated the importance of modelling the closure of funding markets to financial institutions and accounting for liquidity feedbacks within any model of systemic risk. This paper illustrates how such channels are incorporated into a Risk Assessment Model for Systemic Institutions (RAMSI), and outlines how RAMSI can aid assessment of institution-specific and system-wide vulnerabilities.

RAMSI aims to deliver a suite of models that should provide a rigorous and consistent quantitative framework for risk assessment, and help to sharpen the analysis of key vulnerabilities. It will provide a tool for examining the impact of key risks on a bank-by-bank and system-wide basis, and aid in the assessment of the impact of potential policy measures. The results from the suite of models will assist in the communication of risk assessment messages to risk managers in the financial sector, thereby helping shape their attitudes to risk.

The model focuses on the health of core banks in the UK financial system. For these banks, it provides a quantitative framework for assessing how balance sheets dynamically adjust to macroeconomic and financial shocks. The framework allows for macro-credit risk, interest and non-interest income risk, network interactions, and feedback effects arising on both the asset and liability side of the balance sheet. Systemic risks stem from the connectivity of bank balance sheets via interbank exposures (counterparty risk); the interaction between balance sheets and asset prices (fire sale effects); and confidence effects that may affect funding conditions.

The crisis afflicting banks in the United Kingdom and internationally has illustrated the importance of funding liquidity risk, which is captured through two complementary channels. First, an empirical model is used to project individual bank credit ratings, and assess how funding costs may change with the fundamentals of a bank. Second, a ‘danger zone’ model is used, in which a range of indicators determine whether a bank suffers stress so severe that it is shut out of unsecured funding markets.

The model is applied to the UK banking system based on the balance sheet vulnerabilities that existed at the end of 2007, and the results show how rising funding costs and liquidity concerns can amplify other sources of risk. The outputs are generated by running 500 simulations capturing different outturns for the macroeconomy on a three-year forecast horizon. It should be emphasised that the results are illustrative, reflecting model properties in this preliminary

version rather than being the authors' view of the likely impact on the banks in question. In terms of aggregate results for variables such as system-wide profits and total assets, there is some evidence of bimodality, insofar as there are a number of observations in the extreme tail of the distributions, which are typically associated with one or more banks failing.

The unified modelling approach demonstrates how a failing bank may trigger contagion by defaulting on interbank liabilities, selling assets in a fire sale, and undermining confidence in other similar banks. A single, extreme draw is dissected to illustrate these channels. In it, one bank defaults for fundamental reasons but causes two other banks to fail. The second bank fails because its existing vulnerabilities are exacerbated by a drain in confidence in its funding position as it is perceived to be similar to the first failed bank. And the third bank fails because it suffers counterparty losses on the interbank market and endures mark-to-market losses on its assets as a result of the depressing effect on market prices caused by the fire sales of the other two failing banks. The simulations do not incorporate any regulatory or other financial stability policy intervention. The model therefore provides an assessment of how the financial system might fare without any specific policy response.

Further development is planned to extend the model in a number of areas. A substantial area for further work is to analyse banks' cash-flow constraints and consider how defensive actions in the face of funding stress may affect the rest of the financial system and the wider macroeconomy. Another key challenge is to incorporate feedbacks from the banking sector to the real economy.

Ultimately, the future development of the RAMSI framework will be determined to a large degree by the aspects of the model that are found to be most useful in enhancing understanding and communication of financial vulnerabilities. It is envisaged that RAMSI's analytical framework will become useful in the analysis of systemic risk in the United Kingdom, and perhaps in some other countries as well.

1 Introduction

The global financial crisis of 2007-09 has illustrated the importance of including funding liquidity feedbacks within any model of systemic risk. This paper illustrates how we have incorporated such channels into a Risk Assessment Model for Systemic Institutions (RAMSI), and outlines how RAMSI can aid assessment of institution-specific and system-wide vulnerabilities. The model focuses on the health of core banks in the UK financial system. For these banks, the model provides a quantitative framework for assessing how shocks transmit through balance sheets, allowing for macro-credit risk, interest and non-interest income risk, network interactions, and feedback effects arising on both the asset and liability side of the balance sheet. Systemic risks stem from the connectivity of bank balance sheets via interbank exposures (counterparty risk); the interaction between balance sheets and asset prices (fire sale effects); and confidence effects that may affect funding conditions.

Central banks and regulators are increasingly seeking to use formal models to support their financial stability work, and various approaches have emerged in recent years (Jenkinson (2007)). Senior policymakers at the Bank of England have for some time expressed a desire for an integrated approach to assessing systemic risk (Gieve (2007)). Gai and Haldane (2006) provide motivation for a new approach which emphasises the importance of distinguishing probability and impact when conducting risk assessment work, and the Bank of England's preliminary implementation of such a framework is discussed by Haldane *et al* (2007).

RAMSI aims to deliver a suite of models that should provide a rigorous and consistent quantitative framework for risk assessment, and help to sharpen the analysis of key vulnerabilities. RAMSI will provide a tool for examining the impact of key risks on a bank-by-bank and system-wide basis, and will be of help in assessing the impact of potential policy measures. The results from the suite of models will help in communicating risk assessment messages to risk managers in the financial sector, thereby helping shape their attitudes to risk.

The analytical foundations of RAMSI draw in particular on two strands of literature. First, it employs elements of the traditional stress-testing literature, which tends to focus on credit risk on a bank's balance sheet (see Borio and Drehmann (2009) and Foglia (2009)). Second, it draws on recent theoretical work on modelling systemic financial crises. Allen and Gale (2000) explore the spread of contagion in a banking network and Cifuentes *et al* (2005) examine how default across the network is amplified by asset price effects. Gai and Kapadia (2009) examine the non-linearities implied by these externalities and suggest that financial innovation may have increased the severity of crises.[1]

RAMSI's modular approach involves feeding shocks and scenarios from a macroeconomic model through several distinct balance sheet based models that describe how risk profiles evolve throughout banks' operations. The approach is influenced by a framework developed by the Oesterreichische Nationalbank for the Austrian banking system (OeNB (2006) and Elsinger *et al* (2006a)), which integrates balance sheet based models of credit and market risk with a network model to evaluate the probability of bank default. In presenting a prototype version of RAMSI, Alessandri *et al* (2009) extended and developed the single-period Austrian model in a number of dimensions. In a multi-period setting, they incorporated net interest income and feedback effects associated with asset fire sales following bank default.

This paper extends the RAMSI prototype in several ways, including the use of richer balance sheets, a more powerful macroeconomic model, better modelling of credit risk, and a model of non-interest (non-trading) income. But the main innovation in this paper relates to the role of liability-side feedbacks. We develop a two-pronged framework for modelling funding liquidity risk. In the first stage, we apply an empirical model to project individual bank ratings, and use the results to calibrate how funding costs may rise if the position of a bank worsens. In the second stage, we calibrate the onset of funding crises and outright closure of funding markets to particular institutions based on a series of indicators. To inform our analysis, we draw on theoretical models, information from banks' own liquidity policies and evidence from past episodes of funding stress including recent experience, such as the failure of Northern Rock.

RAMSI's framework is particularly attractive because of its 'storytelling' capacity. Alternative approaches to the analysis of systemic risk offer particular strengths, either in terms of micro-foundations,[2] or in terms of consistency with market-based pricing of risk.[3]

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[1] This result is reinforced by Gai *et al* (2008) who demonstrate how financial innovation and macroeconomic stability may have intensified the robust yet fragile nature of the banking system.
[2] For example, Goodhart *et al* (2006) provide a general equilibrium framework, but the model is stylised and difficult to operationalise.
[3] The 'asset pricing' approach extracts risk from observed security prices. This approach can be applied to individual banks (Segoviano and Padilla (2006); Elsinger *et al* (2006b) and Frisell *et al* (2007) or to sectors of the economy (Gray *et al* 2007)). These models provide timely updates to banks' risk profiles, albeit on the basis of strong assumptions on market completeness and efficiency. Furthermore, market prices may embed the possibility of official support, so the asset-pricing approach may be unable to identify the extent to which intervention helps to mitigate systemic risks (Birchler and Facchinetti (2007)).

Although RAMSI's framework relies on reduced-form estimation and behavioural 'rules of thumb', it offers a flexible and operational means of capturing a wide range of risks and transmission channels, and allows for a more articulated analysis and interpretation of the outputs of stress-testing exercises.

The structure of the paper is as follows. Section 2 describes the current components of RAMSI and explains how they fit together. Section 3 discusses the aggregate distributions obtained from stochastic simulation and conducts a detailed analysis of a particular realisation in which funding liquidity feedbacks contribute to system-wide stress. Section 4 discusses how RAMSI can improve the quality of risk assessment work, and Section 5 concludes.

2 The modelling framework

2.1 Overview, sequencing and balance sheets

Figure 1 illustrates the modular structure of RAMSI and the mapping from shocks to systemic risk. The transmission dynamics hinge crucially on two factors – the nature and scale of shocks and the structural characteristics of the financial system. In such an environment, balance sheet interdependencies and asset and liability-side feedbacks make for complex, non-linear behaviour. RAMSI produces asset distributions for individual banks and for the aggregate banking system by linking together the shaded modules presented in Figure 1. The unshaded module – feedbacks to the macroeconomy – is mentioned briefly in the conclusion but left for future work. In what follows, we discuss the overall modelling strategy in RAMSI before briefly discussing each of its components.

At the core of RAMSI are detailed end-2007 balance sheets of the largest UK banks (ten at end-2007).[4] The balance sheets are highly disaggregated, with approximately 650 balance sheet entries (including 400 asset classes and 250 liability classes). Each of the asset and liability classes is further disaggregated into five maturity buckets and six repricing buckets.[5] This modelling of individual bank balance sheets supports an analytically rich model and allows us to examine, in detail, the likely sources of profits and losses on a disaggregated and aggregated basis. Data are mainly extracted from published accounts but are supplemented from regulatory

[4] Membership of the major UK banks group is based on the provision of customer services in the United Kingdom, regardless of country of ownership. At end-2007, the members were: Alliance & Leicester, Banco Santander, Barclays, Bradford & Bingley, Halifax Bank of Scotland, HSBC, Lloyds TSB, Nationwide, Northern Rock and Royal Bank of Scotland.
[5] We do not have six repricing buckets for each of the five maturity buckets.

returns. As some balance sheet entries are unavailable, we use rules of thumb based on other information or extrapolations on the basis of our knowledge of similarities between banks to fill in the data gaps. Much of the granularity arises from decomposition of the trading book and available for sale (AFS) assets. Since the focus of this paper is on the role of funding liquidity risk, we do not model these exposures here. However, this part of the balance sheet has played an important role in the ongoing financial crisis, and we believe that no systemic risk model can credibly ignore it. Trading book and AFS models are currently under development and will be introduced in the next version of RAMSI.

The model is run over a three-year horizon, sufficient time for some adverse shocks to be reflected in credit losses (Bunn *et al* (2005) and DNB (2006)), and consistent with the horizon central banks often use when stress testing their financial systems (Hagen *et al* (2005), Bank of England (2007) and Sveriges Riksbank (2007)). The sequence of events is illustrated in Figure 2. Outcomes from a macroeconomic model determine a yield curve and probabilities of default and loss given default on banks' credit exposures. For each combination of risk factors, we model the first-round effects on each bank, with distinct modules accounting for credit losses, net interest income, and other income and operating expenses.

If the fundamentals of a bank deteriorate, its credit rating may be downgraded, increasing its future funding costs. In severe circumstances, funding conditions may deteriorate to such an extent that the bank is shut out from short-term funding markets. It then fails, triggering a feedback loop. Because of bankruptcy costs, a fraction of the failed bank's assets are lost, reducing the amount available to its creditors on the interbank network. Some of the bank's assets are sold at fire sale prices, creating asset-side feedbacks that cause remaining banks to suffer temporary (intra-period) mark-to-market losses. Funding markets suffer 'confidence contagion' that renders banks with similar characteristics to the failed bank more vulnerable to being shut out of funding markets. If a further bank fails after we account for the second-round effects, then the loop repeats until the default cascade ends.

Figure 1: RAMSI framework

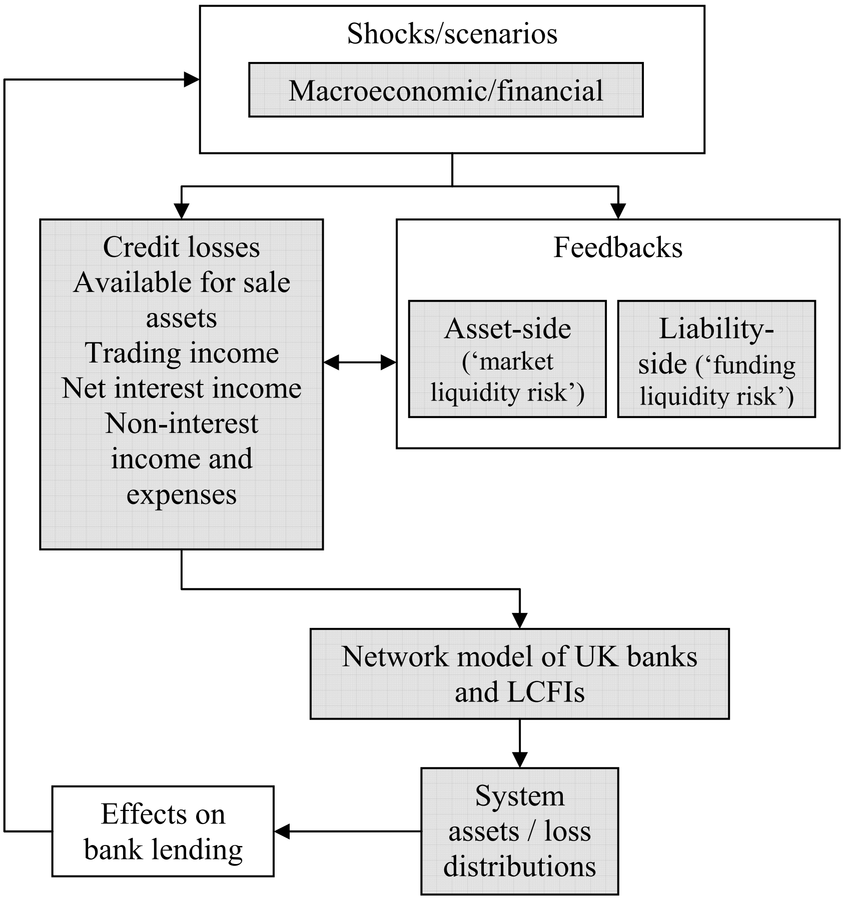
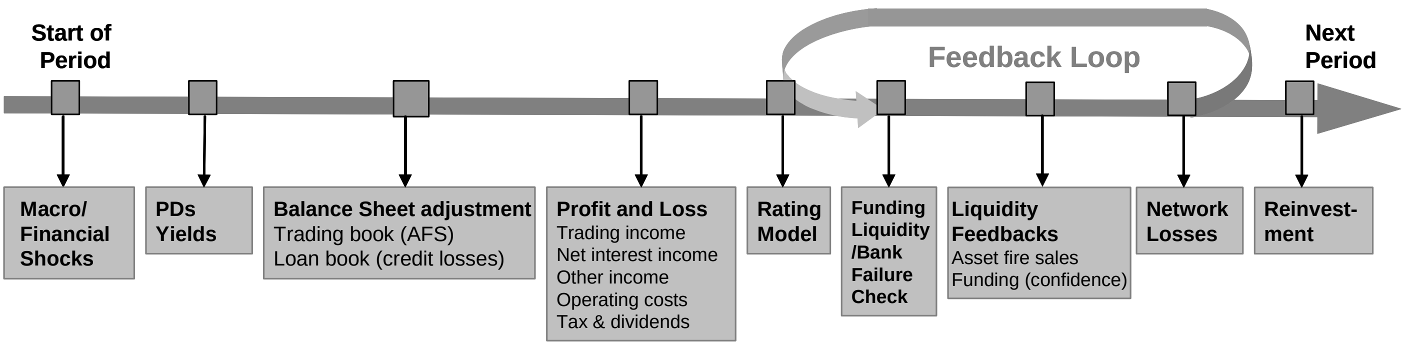


Figure 2: Model dynamics*



* The trading book and available for sale (AFS) assets are not included in this version of RAMSI.

In the absence of bank failures (or after the feedback loop has completed), we update the balance sheets of surviving banks using a rule of thumb for reinvestment behaviour. Banks are assumed to target pre-specified Tier 1 capital ratios, and invest in assets and increase liabilities in proportion to their shares on their initial balance sheet.

Throughout the paper, we assume that there is no regulatory or other policy intervention, aside from an interest rate response that is endogenous to the macroeconomic model. This is partly because modelling the policy reaction to extreme events is inherently difficult, especially given that there is no single, standard response to financial crises. The model therefore provides an assessment of how the financial system would fare without any specific policy response. This allows for judgements to be drawn on the potential benefits and costs of intervening.

2.2 The macroeconomic model

The link between the macroeconomy and the various risks on banks' balance sheets is central to RAMSI. We use a large-scale Bayesian VAR (BVAR) to capture the evolution of macroeconomic and financial variables. The BVAR is the only source of shocks in RAMSI, thereby preserving a one-for-one mapping from macroeconomic variables to default risk, which is useful for story telling purposes.[6]

The BVAR is estimated on quarterly data over the sample period 1972 Q2-2007 Q4. The model includes 24 domestic and foreign (US and EU) variables (see Table 1) and has two lags. We use quarterly growth rates of all variables, barring those denoted with an asterisk. The resulting vector of time series variables to be modelled therefore contains a mixture of levels and growth rates (quarterly GDP growth, the level of the three-month T-bill rate etc). Our prior treats every variable in the system as a white noise process centred around a constant. This is a special case of the Minnesota prior popularised by Litterman (1986): essentially, we adapt the standard Minnesota prior to the case where all unit roots have been eliminated by data transformations.[7]

The BVAR performs well according to usual diagnostics. First, it has reasonable in-sample fit, capturing much of the variation over time in most series – the average R^2 across the 24 equations was 66%. The equations for asset prices had the poorest fit: equities, sterling ERI, and particularly oil prices (R^2 of 12%). Second, for the most part, the forecasts are reasonable: most variables are projected to either regress back to their average historical growth rates, or to gradually converge on their sample means. Third, the model also produces reasonable impulse responses following shocks to UK GDP, UK three-month interest rates, UK house prices and real oil prices.

[6] It is, of course, possible to run stress scenarios in order to determine the impact of adjusting non-macro variables and model parameters.
[7] In a Bayesian context, all parameters are treated as random variables and the data are used to estimate their probability distribution rather than to obtain point estimates. We abstract from model uncertainty and use the means of the estimated posterior parameter distributions.

Table 1: List of BVAR variables

United Kingdom	**United States**
Real GDP	Real GDP
CPI inflation	CPI
£ERI	3-m T-bill rate*
Real FTSE All-Share	10-yr govt bond rate*
3-m T-bill rate*	
3-yr govt bond rate*	**Euro area**
10-yr govt bond rate*	Real GDP
Unemployment*	CPI
Real house prices	3-m T-bill rate*
Real comm. prop. prices	10-yr govt bond rate*
Income gearing*	
Corporate lending*	**World**
3-m Libor spread*	Real oil prices
10-yr corporate spread*	Real world equity prices

For simplicity, we approximate the yield curve by linearly interpolating the short and long-term interest rates implied by the BVAR (two for the United Kingdom and one each for the euro area and United States). This is the source of all risk-free rates used in the model. And, since the BVAR does not forecast the Libor spread particularly well, we currently assume that it evolves according to the path implied by forward spreads.

2.3 *First-round impact on banks*

2.3.1 *Credit risk*

The credit risk module treats aggregate default probabilities (PDs) and loss given default (LGD) as a function of the macroeconomic and financial variables from the BVAR. Credit losses are derived as the product of the relevant aggregate PD times LGD times each bank's total exposure to the sector,[8] though we adjust the aggregate write-off rate for each bank to account for heterogeneity in the riskiness of banks' portfolios.[9] We model credit losses arising from exposures to UK households (mortgages, credit card, and other unsecured borrowing), UK

[8] That is, we model 'expected credit losses', and trace out variation in expected credit losses driven by macro fundamentals.
[9] These adjustments are made on the basis of historical differences between write-off rates of individual banks and aggregate write-off rates. This implies that a relatively 'safer' bank continues to incur lower credit losses than the typical bank.

corporates, plus households and corporates in the United States, euro area and rest of the world.[10] For brevity, we only discuss results for UK mortgages and corporate loans.

Basing the model on Whitley *et al* (2004), we relate the PD on a representative pool of mortgages to the unemployment rate, the level of income gearing (interest payments relative to disposable income), and undrawn equity in housing stock (the residual proportion of housing wealth net of the stock of mortgage debt). Our dependent variable is the fraction of borrowers who are three months or more in arrears. We model arrears as these provide a forward-looking indicator of actual defaults. We estimate a transition rate based on the average historical relationship between these variables. The model is estimated on a sample running from the early 1980s, reflecting the structural change in retail credit markets following the removal of direct controls on bank lending in 1980 (the 'Corset'). The LGD on this pool is assumed to be driven by residential property prices. Our preferred model of the corporate liquidations rate is driven by real output growth, the real (*ex-post*) cost of borrowing, commercial property prices and a measure of the cyclical variation in corporate debt (based on Vlieghe (2001)). The LGD on a corporate loan is assumed to depend on the value of commercial property prices.

Mortgage arrears

$$\ln\left(PD_t^{secured}\right) = \underset{(8.10)}{2.53} - \underset{(-19.93)}{6.03}\ln\left(undrawn_{t-4}\right) + \underset{(11.18)}{0.72}\ln\left(u_{t-4}\right) + \underset{(18.87)}{2.03}\ln\left(gearing_{t-4}\right)$$

Sample: 1981 Q1 – 2007 Q4

$$LGD_t^{secured} = LGD_{t-1}^{secured} - \frac{1}{3}\left(\Delta\ln\left(houseprice_t\right)\right)$$

Corporate liquidations

$$\ln\left(PD_t^{corp}\right) = -\underset{(-3.92)}{0.14} - \underset{(-6.08)}{6.53}\ln\left(\frac{GDP_t}{GDP_{t-4}}\right) + \underset{(7.46)}{0.07}\,r_{t-1} + \underset{(7.12)}{0.06}\,r_{t-4} - \underset{(-8.58)}{2.13}\ln\left(\frac{comm\_property_t}{comm\_property_{t-4}}\right) + \underset{(2.80)}{0.99}\ln\left(debt_{t-8}\right)$$

Sample: 1978 Q1 – 2004 Q4

$$LGD_t^{corp} = LGD_{t-1}^{corp} - \Delta\ln\left(commprice_t\right)$$

The equations for mortgage arrears and corporate liquidations are shown above.[11] The estimated coefficients in both equations are all signed according to our priors. Both models capture the broad movements in the data reasonably well, but there are clear areas for improvement. The mortgage arrears equation, for instance, only accounts for around half of the pickup in arrears in

[10] Data availability poses a major challenge. It would be desirable to capture sectoral concentrations by modelling a finer breakdown of exposures (commercial property lending etc) and incorporate lumpiness in corporate exposures (we currently assume that portfolios are infinitely granular).

[11] The equations are under continued development and are not identical to those used to underpin the *Financial Stability Report* or other published analysis.

the early 1990s. And the performance of the corporate PD equation deteriorates from 2002 onwards.[12]

2.3.2 *Net interest income*

For most of the loan book, interest income is modelled endogenously. Banks price their loans on the basis of the prevailing yield curve and the perceived riskiness of their debtors: an increase in actual or expected credit risk translates into a higher cost of borrowing. However, banks' repricing ability is constrained by the maturity structure of their balance sheets. Since assets and liabilities typically do not have matched maturities, these constraints generate significant income risk. The possibility of shifts in the yield curve intensifies this risk.

We use the risk-neutral asset-pricing model of Drehmann *et al* (2008) to capture both sources of income risk in a consistent fashion. Consider a risky asset, *A*, with a repricing maturity equal to *T*, implying that the asset pays a fixed coupon *C* over the next *T* periods. The economic value of the asset today is the risk-adjusted discounted value of future coupon payments and the principal:

$$EV(A_0) = \sum_{t=1}^{T} D_t C A_0 + D_T A_0 \, , \tag{1}$$

where the discount factors are given by:

$$\begin{aligned} D_t &= \prod_{l=1}^{t} (1 + R_{l-1,l})^{-1} \\ R_{l-1,l} &= \frac{r_{l-1,l} + PD_{l-1,l} * LGD_{l-1,l}}{1 - PD_{l-1,l} * LGD_{l-1,l}} \end{aligned} \tag{2}$$

and $r_{l-1,l}$, $PD_{l-1,l}$, $LGD_{l-1,l}$ represent respectively the forward risk-free interest rate, expected PD and expected LGD between time *l-1* and *l*.[13] We can use the first equation to calculate a 'fair' time-zero coupon that guarantees that $EV(A_0) = A_0$:

$$C = (1 - D_T) / \sum_{t=1}^{T} D_T \tag{3}$$

Whenever the bank can update *C* (at time *T*, *2T*,...), it will do so using the equation above, so that expected interest income covers expected losses and book and economic value coincide. Between *0* and *T*, though, interest rates, PDs and LGDs may change whereas the coupon is

[12] Possible explanations include: the (until recent) prolonged stability of the macroeconomy; the cleansing effect of earlier recessions; legislative changes (the 2000 Insolvency Act and 2002 Enterprise Act); and the (until recent) easy availability of credit.
[13] The risk-free yield curve is known at the time of pricing; we assume that banks take future PDs and LGDs to be equal to the most recent observations.

fixed: any change in discount factors that is unexpected as of time-zero will thus prevent the zero profit condition from holding. For each bank, we use balance sheet information to determine the fraction of assets and liabilities that can be repriced at any point in time. The model implies that the pricing structure of the balance sheet, and particularly the mismatch between assets and liabilities, influences a bank's vulnerability to interest rate and PD shocks.

The model-implied coupons are calibrated to better accord with actual observed spreads as these may also partly reflect compensation for fixed costs associated with arranging loans and other profits derived by banks. For example, the model-implied coupon on mortgages is increased by 80 basis points.

For other parts of the balance sheet, including all of the liability side, we simply calibrate spreads based on market rates and other data. For example, we assume that interbank assets and liabilities receive/pay the risk-free rate plus the Libor spread, while banks pay negative spreads relative to the risk-free rate on some household and corporate deposits (if the negative spread implies a negative interest rate, the interest rate paid is assumed to be zero). As discussed below, spreads on certain liability classes may also depend on the credit rating of the bank in question.

2.3.3 Non-interest (non-trading) income and operating expenses

Non-interest, non-trading income (henceforth non-interest income) was just under half of UK banks' operating income in 2007.[14] It includes fees and commissions (see Table 2). Stiroh (2004) finds non-interest income to be procyclical, which appears plausible given that its components include securitisations. Bank-specific and structural determinants may also be important. The rise in the share of non-interest income may be seen in the context of new intermediation technologies such as internet fees; financial derivatives; loan securitisations; or by selling back-up lines of credit. Capital is not required for many such fee-based activities, even though some, such as derivatives and trust services, take place on-balance sheet, so increased reliance on non-interest income could be associated with higher leverage (DeYoung and Rice (2004)).

[14] One reason for separating the modelling of trading income from that of the other components of non-interest income is that trading income is the most volatile. It contributes to a large part of the variance of total non-interest income, which itself has increasingly contributed to the variance of overall operating income growth. Stiroh (2004) showed that for US banks, non-interest income contributed 80% of the volatility of operating income in the 1990s.

Table 2: US and UK non-interest income and expenses (ratio of operating income)[1]

United States	1984-89	1990-99	2000-07	United Kingdom[2]	1997-03	2004-06	2007 interim
Net interest income	0.72	0.64	0.57	Net int. inc.	0.58	0.42	0.39
Non-interest income	0.28	0.36	0.43	Non-int. inc.	0.43	0.58	0.61
Fiduciary	0.05	0.05	0.05	Net fees & com	0.27	0.20	0.21
Service charge	0.06	0.07	0.07	Dividend income	0.003	0.004	0.005
Trading	0.02	0.03	0.03	Dealing profits	0.05	0.11	0.13
Other	0.15	0.21	0.27	Other	0.10	0.27	0.26
Non-int. expenditure	0.68	0.64	0.59	Non-int. exp.	0.56	0.62	0.59
Memo:							
Non-int, non-trad. inc	0.26	0.33	0.40	Non-int, non-trad. inc	0.38	0.47	0.48

[1] A caveat is that the components of non-interest income are not directly comparable between the United States and the United Kingdom. For example, fees and commissions are included in other non-interest income in the United States.
[2] In the United Kingdom, the change to International Financial Reporting Standards accounting standards in 2004 boosted the share of insurance income. For example, Lloyds TSB's non-interest income as a share of its operating income jumped from 47% in 2003 to 74% in 2004.

Data paucity and inconsistencies rule out estimation based on UK data and we instead use US data. This seems reasonable given the similarities between the United Kingdom and United States and, in particular, the similar shares of non-interest income as a share of operating income (around 42% for UK banks and 38% for US banks, see Table 2). As in Stiroh (2004), we use aggregate quarterly US data that covers over 7,000 Federal Deposit Insurance Corporation insured commercial banks, covering the period 1984 Q1 to 2007 Q3. The use of aggregate data prohibits a search for bank-specific effects.

The results for the favoured equation are shown below. As in Stiroh (2004), non-interest income is quite strongly procyclical. A 1 percentage point increase in real GDP above baseline implies that real non-interest income rises by 2.7 percentage points initially, and 2.0 eventually.[15] We find insufficiently strong evidence for factors such as balance sheet asset growth, equity returns and equity volatility to include them in RAMSI. However, in some specifications (not shown) there was evidence that non-interest income increases with leverage and decreases with the slope of the yield curve.

[15] We also tried an error correction mechanism specification in attempt to identify a long-run relationship. But it did not forecast as well as the dynamic equation.

$$\Delta \ln\left(\text{Non - interest income}_t\right) = \underset{(0.27)}{0.003} - \underset{(2.94)}{0.338}\,\Delta \ln\left(\text{Non - interest income}_{t-1}\right) - \underset{(2.06)}{0.246}\,\Delta \ln\left(\text{Non} - \text{interest income}_{t-2}\right)$$
$$+ \underset{(0.22)}{0.027}\,\Delta \ln\left(\text{Non} - \text{interest income}_{t-3}\right) - \underset{(0.02)}{0.003}\,\Delta \ln\left(\text{Non} - \text{interest income}_{t-4}\right) + \underset{(3.44)}{2.721}\,\Delta \ln\left(GDP_t\right) + \underset{(1.03)}{0.878}\,\Delta \ln\left(GDP_{t-1}\right)$$
$$- \underset{(0.13)}{0.114}\,\Delta \ln\left(GDP_{t-2}\right) - \underset{(1.61)}{1.357}\,\Delta \ln\left(GDP_{t-3}\right) + \underset{(1.19)}{1.003}\,\Delta \ln\left(GDP_{t-4}\right)$$

Joint significance of GDP and lagged GDP (p - value) : 0.004. Observations. 90. Adjusted $R^2 = 0.18$

We validate the US-based model on UK data by checking its forecasting performance. We generate non-interest income forecasts for each UK bank based on its initial level and increment that with the predicted values of real non-interest income growth from the estimated equation. When calibrated to UK banks, the out of sample forecasting performance is satisfactory. Between 2005 and 2007 the model predicts a 16.5% increase over the two years compared with an outturn of 16.2%.

For non-interest expenses (operating expenses), we suppose that banks target cost ratios. This is supported by empirical estimates of an equation for non-interest costs based on the same aggregate US data that were used to estimate non-interest income. Costs are found to be less procyclical than operating income, reflecting the proposition that banks are unable to immediately adjust expenses. The equation for operating expenses is:

$$\left(\frac{\text{Operating expense}}{\text{Operating income}}\right)_t = \underset{(2.16)}{0.053} + \underset{(23.64)}{0.920}\left(\frac{\text{Operating expense}}{\text{Operating income}}\right)_{t-1} - \underset{(1.45)}{0.487}\, d\ln\left(GDP_t\right)$$

Observations : 94. Adjusted $R^2 = 0.86$

2.3.4 Profits, taxes and dividends

In order to generate plausible profit figures, we assume that each bank earns a trading income that is proportional to the size of its portfolio, using 2007 data to calibrate the ratio. This assumption will obviously become redundant when we introduce trading book and AFS models. Profits are then computed as the sum of all sources of income, net of expenses and credit losses. We deduct taxes and dividends from profits, assuming that the tax rate and ratio of dividends to profits are in line with recent history.

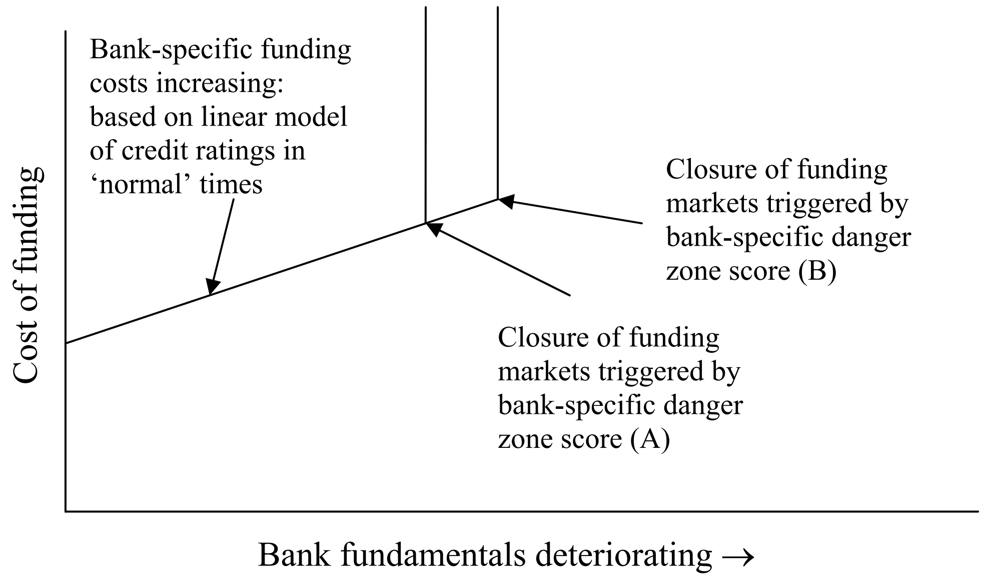
Post-tax, post-dividend profits (or losses) are assumed to increase (or erode) Tier 1 capital directly. Updated Tier 1 capital ratios may then be computed by dividing capital by risk-weighted assets, where the latter are computed by applying Basel II standardised risk weights or approximations to them where we have insufficient information (such as on corporate loans, for which we do not know the ratings of the borrowers).

2.4 Funding liquidity risk and bank failure

The ongoing credit crisis has illustrated starkly how increased funding costs and the closure of funding markets can trigger bank failure. We have integrated two complementary channels to capture funding liquidity effects. First, we apply an empirical model to project individual bank credit ratings, and use the results to calibrate how funding costs may change with the fundamentals of a bank. Second, we use a separate 'danger zone' model in which a range of indicators determine whether a bank suffers stress so severe that it is shut out of unsecured funding markets.

We consider it important to model the outright closure of funding markets in a distinct framework. Figure 3 illustrates this point. Though there may be a relatively linear relationship between a deterioration in bank fundamentals and increased funding costs in relatively 'normal' times, it is hard to use this approach to identify the closure of funding markets in extreme circumstances given that this is an inherently non-linear process, and could occur at different ratings and funding costs (A or B), depending on the circumstances. Hence we feel that the danger zone approach is more appropriate for identifying the region in which funding markets are likely to shut. Nevertheless, we intend to use the funding cost/ratings model as a cross-check on the danger zone approach.

Figure 3: The operation of funding liquidity risk



2.4.1 Bank ratings and funding costs

We model banks' funding costs in two stages. First, we use an ordered probit model (adapted from Pagratis and Stringa (2009)) to examine the sensitivity of Moody's senior (long-term) unsecured ratings to a number of key bank performance indicators and macroeconomic variables. The index produces ratings for each bank at each quarter using the estimated coefficients from Table 3. Ratings are found to improve when: (i) profitability increases; (ii) the higher the market share of lending by a bank; (iii) the higher the cost efficiency (proxied by operating expenses/total assets); (iv) the higher the asset quality (proxied by credit losses/net interest income); (v) economy-wide output and credit rise above trend, and the yield curve steepens.

Table 3: Ordered probit estimated coefficients for the bank ratings model

The model is estimated using a data panel of 1,369 observations, for the period 1999-2006. The data panel includes published accounts data of 293 banks from 33 countries (grouped in 14 regions), and macroeconomic information. The constant (6.187) is the sum of coefficients for the UK regional dummy (0.441), the Aaa-Aa1 sovereign rating dummy (6.809), a dummy for IFRS reporting by banks (-0.577) and a dummy for the 4th quartile in the banks' sample distribution ranked by total assets.

		Investment-grade bank		*Sub investment-grade bank*	
DEPENDENT VARIABLE: *Bank senior unsecured rating by Moody's*	*Number of lags (in years)*	Coefficient	Robust std. error	Coefficient	Robust std. error
INDEPENDENT VARIABLES:					
BANK FINANCIAL INDICATORS					
Profitability: 100*(Profits before tax + Credit losses) / Total assets	1	0.200***	0.075	0.048**	0.076
Asset quality: 100*Credit losses / Net interest income	1	-0.002***	0.001	-0.002***	0.001
Cost efficiency: 100*Operating expenses / Total assets	0	-0.127***	0.039	-0.127***	0.039
Funding gap: 100*(Customers loans – Short-term liabilities) / Customer loans	0	-0.002***	0.000	0.002***	0.000
Market share: ln(100*Loans / Total loans by banks in the network)	0	0.179***	0.050	0.179***	0.050
Capital dummy: 1 if (Equity / Total assets) falls below target, 0 otherwise	0	-0.261***	0.064	-0.261***	0.064
MACROECONOMIC VARIABLES					
Yield curve slope: (10-year gov. bond rate) – (3-month T-bill rate)	1	0.078***	0.030	0.078***	0.030
Economic downturn dummy: 1 if real output gap is negative, 0 otherwise	1	0.054	0.084	0.054	0.084
Credit boom dummy: 1 if credit gap is positive, 0 otherwise	2	0.038	0.087	0.038	0.087
Economic downturn * Credit boom	1,2	-0.222**	0.109	-0.222**	0.109
Sub investment-grade dummy: 1 if rating Baa2 and below	1	-	-	-3.038***	0.119
Constant	-	6.187***	-	6.187***	-

Note. **significant at 5%; ***significant at 1%. The first column in Table3 reports the lag structure of explanatory variables in the adapted Pagratis and Stringa (2009) model. For interaction effects we report two lags, one for each interacting variable. The second column reports the estimated coefficients of explanatory variables in the model. The third column reports White robust standard errors. The fourth column reports the estimated coefficients of interaction effects between explanatory variables and a dummy that takes the value 1 if the banks previous rating was of sub investment grade (Baa2 and below) and 0 otherwise. Note also that we have replaced the insignificant coefficients on the economic downturn dummy and the credit boom dummy to be zero in the code.

The assigned ratings are mapped to credit spreads using Merrill Lynch's indices of UK sterling bond spreads associated with different credit ratings. These bank-specific spreads are applied to certain types of wholesale funding (including interbank and other non-retail deposits, commercial paper, certificates of deposit, and subordinated debt). This introduces a key feedback mechanism on the liability-side of balance sheets: if a bank gets downgraded, the associated rise in its funding costs will reduce its future profitability, leaving it more vulnerable to future downgrades and, ultimately, to a loss of access to wholesale funding markets.

2.4.2 Modelling the closure of funding markets – a 'danger zones' approach

Modelling the outright closure of funding markets presents significant challenges, both because of the binary, non-linear nature of liquidity risk, and because liquidity crises in developed countries have been (until recently) rare events for which data are limited. We therefore adopt a simple, transparent (yet subjective) 'danger zone' approach under which banks accumulate points as liquidity conditions deteriorate, and face the prospect that certain funding markets may close to them as their score crosses particular thresholds.

Figure 4: Closure of funding markets in RAMSI

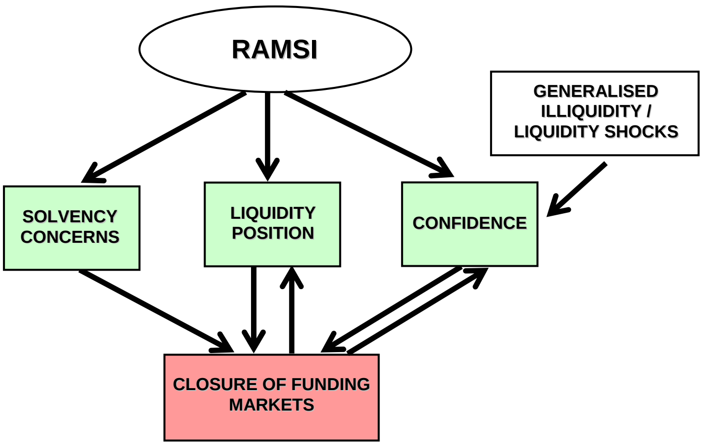


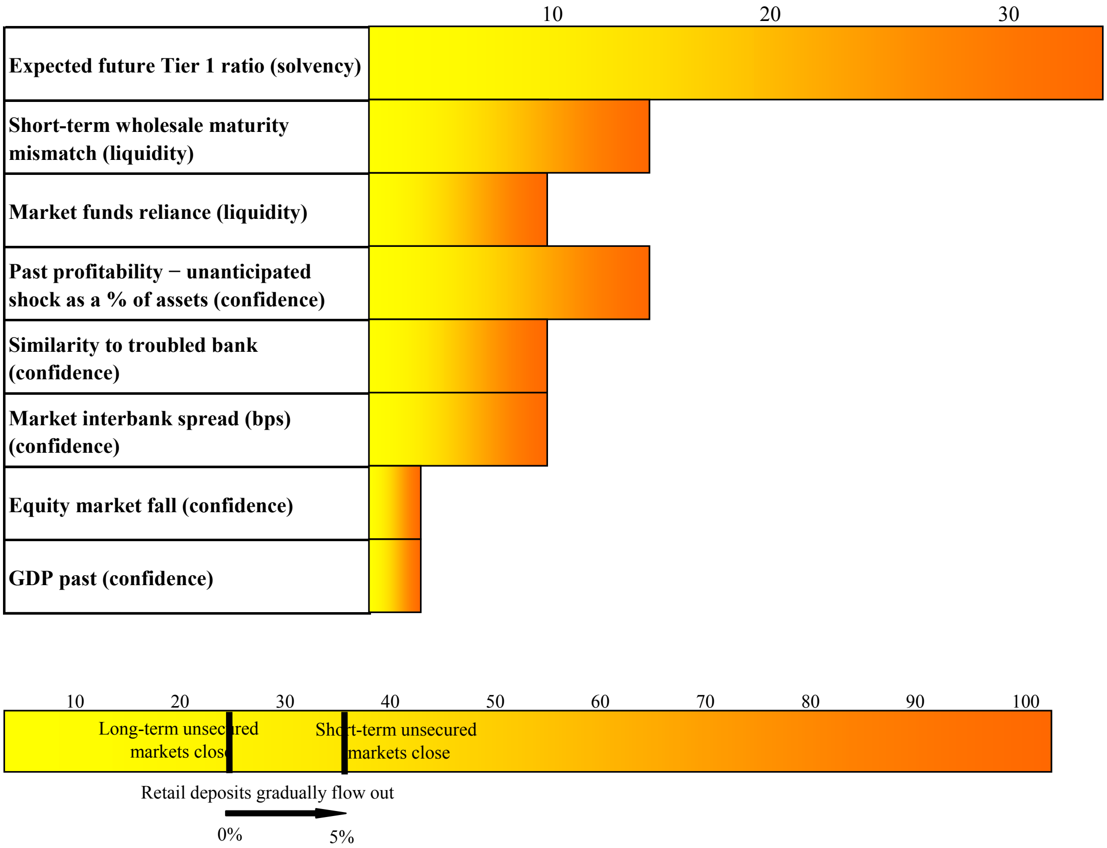
Figure 4 gives an overview of the approach. Outputs from the rest of the model are mapped into specific indicators of funding stress relating to three key areas that theoretical models (Chen (1999) and Goldstein and Pauzner (2005)) and evidence from case studies and banks' own liquidity policies suggest are important – solvency, liquidity and confidence. The framework allows for feedback effects. In particular, the closure of certain funding markets to an institution: (i) may worsen that bank's liquidity position through 'snowballing effects', whereby the bank becomes increasingly reliant on short-term funding; and (ii) may adversely affect 'similar' banks through a pure confidence channel. Recent events have emphasised that market-wide liquidity factors can also play an important role in affecting confidence and hence contributing to funding stress. To proxy for these factors, the framework captures a greater risk of funding stress in periods when the market interbank spread is elevated.

Figure 5 presents the set of eight indicators (the underlying factor that each is trying to proxy is mentioned in brackets), along with the aggregation scheme and the thresholds at which short-term and long-term unsecured funding markets are assumed to close to the bank.[16] In constructing the weighting, we place roughly equal weight on three main factors that can trigger funding crises: (i) concerns about future solvency; (ii) a weak liquidity position/funding structure (for example, high reliance on short-term wholesale unsecured funding); and (iii) institution-specific and market-wide confidence effects, over and above those generated by solvency concerns or weaknesses in liquidity positions. In the aggregation, we allow for the possibility that a run could be triggered either by extreme scores in any of the three areas, or by a combination of moderate scores across the different areas. The judgements underpinning more specific aspects of the calibration and weighting schemes were informed by analysis of a range of case studies.[17]

Currently, the danger zones are incorporated into RAMSI in a simplified way. Since the model does not yet include model-consistent expectations, the current Tier 1 capital ratio is used instead of the expected ratio and the past profitability indicator is ignored as it is not possible to identify unanticipated losses. In addition, the threshold at 25 points is ignored and banks are simply assumed to default if their danger zone score reaches 35 and short-term unsecured markets close to them. When fully incorporated, a score of 25 or more will trigger the closure of long-term unsecured funding markets to the bank, which will be able to refinance in short-term unsecured funding markets or take other defensive actions such as selling or repoing assets. There will be no default at this point but there will be a snowballing effect, whereby the increased reliance on short-term funds will affect the bank's score on the maturity mismatch indicator.

[16] Secured funding markets are discussed below. For simplicity, we do not consider a more detailed breakdown of funding markets (for example, we do not distinguish between foreign and domestic funding markets).
[17] Development of case studies is still work in progress and full details of the weights used will be published once complete. The case studies will aim to cover both episodes in which banks have failed (Franklin National Bank, Continental Illinois, Japanese banks and Northern Rock) and episodes in which banks have survived (Lehman Brothers during the LTCM crisis and Société Générale following the recent fraud).

Figure 5: Danger zones – basic structure

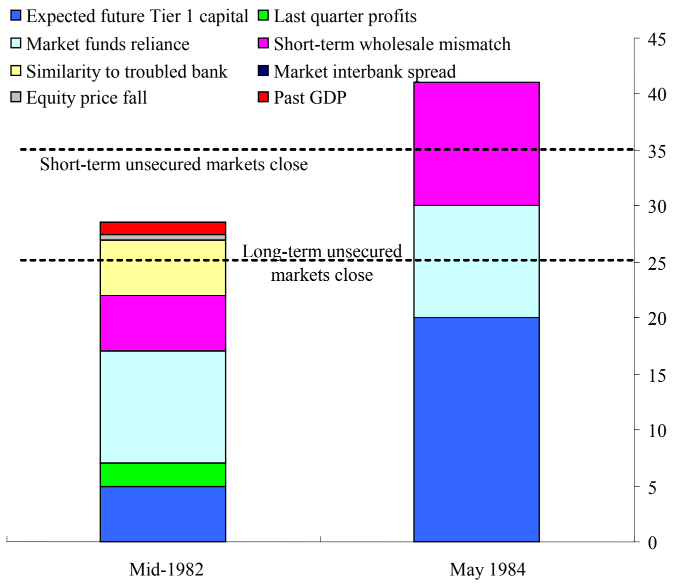


The full danger zone framework will also allow for a number of extensions. First, there will be a gradual outflow of retail deposits after long-term unsecured funding markets close to the bank, such that the outflow reaches 5% of retail deposits by the time short-term unsecured markets close. This is intended to reflect behaviour of well-informed investors rather than a widespread (Northern Rock style) run. Second, we intend to define banks scoring less than five points as ‘safe’ and allow them to receive funding withdrawn from troubled banks; as such, they will help to close the system by capturing flight-to-quality effects. If there are no ‘safe’ banks, we will assume that funds end up as increased reserves at the central bank. Finally, we plan to extend the framework to cover secured funding markets. For these, we will assume that if a bank cannot repo assets, it will be able to sell them at the prevailing market price. Critically, however, this could be a fire sale price and, in some instances, could even be zero, either because there are no buyers in the market or because of potential stigma effects which could be generated by a large asset sale in an illiquid market. The framework will thus highlight the importance of collateral quality in determining how a bank fares if secured funding markets close to it.

2.4.3 *Example of a danger zone calibration: Continental Illinois*

Case studies indicate that the danger zones approach performs relatively well, especially in terms of capturing the ranking of institutions under most stress. We have considered case studies beyond the very recent crisis. An example is the case of Continental Illinois, which, at least in terms of funding liquidity pressure, can be divided into two periods: the closure of longer-term domestic funding markets to it in July 1982 and the global run in May 1984. Chart 1 scores Continental Illinois in each of these periods.

Chart 1: Continental Illinois danger zone points



Continental scores heavily on the market-funds reliance indicator. But solvency concerns also played a crucial role for Continental. In particular, the July 1982 run may be identified with mild concerns over future solvency stemming from anticipated losses on risky speculative loans to the energy sector. Many of these loans had been originated by Penn Square, a much smaller bank which failed earlier that month.

Aside from rising solvency concerns, Continental scores points following Penn Square's failure both because of its similarity and because of a significant unanticipated loss due to a direct exposure. Overall, Continental scores enough points for the first danger zone threshold to be crossed. Increased reliance on short-term funding then serves to increase Continental's score over the next couple of years. But the final trigger for the second run is the fallout from the

Latin American debt crisis – this substantially raised future solvency concerns during the first part of 1984 so that by May, Continental exceeds the second danger zone threshold.

2.4.4 *Bank failure and bankruptcy costs*

As just discussed, banks are assumed to default if they score 35 danger zone points and are shut out of short-term unsecured funding markets. When a bank defaults, we follow James (1991) and suppose that it incurs costs equivalent to 10% of its remaining assets. This is also in line with the mean figure reported in Bris *et al* (2006). These bankruptcy costs are designed to capture the direct legal, accounting and redundancy costs which are incurred upon default. They may also be viewed as capturing the erosion in the real value of a bank's assets that may occur upon default due to disruptions to established bank-borrower relationships or the loss of human capital. They imply that even if banks fail with positive shareholder funds, they will be unable to fulfil all of their obligations upon default.

2.5 *Second-round effects and contagion*

2.5.1 *Asset side feedbacks: fire sales*

When a bank is in distress, it may sell assets, opening up the possibility of an important feedback channel operating via asset prices. In the current version of RAMSI, such fire sales only occur after a bank defaults, and not as a defensive action to stave off failure. A failing bank is assumed to liquidate all its AFS assets. The fire sale discount lasts for one quarter, and the resulting fall in asset prices may lead other banks to incur mark-to-market losses; hence in extreme circumstances these banks may then also fail.

The associated price impact given by equation **(4)** is applied to other banks' AFS assets. Consistent with Duffie *et al* (2007), we take the relationship between prices and the magnitude of fire sales to be concave. For asset j, the fire sale equation is:

$$P_j' = \max\left\{0, P_j\left(2 - \exp\left(\theta \frac{S_{ij}}{M_j + \varepsilon_j}\right)\right)\right\} \qquad \textbf{(4)}$$

The price of asset j following the fire sale, P_j', is the maximum of zero and the price before the fire sale, P_j, multiplied by a discount term. The discount term is a function of value of assets sold by bank i in the fire sale, S_{ij}, divided by the depth of the market in normal times, M_j, and scaled by a parameter θ that reflects frictions, such as search problems, that cause markets to be less than perfectly liquid. Market depth can also be shocked by a term ε_j to capture fluctuations in the depth of markets as macroeconomic conditions vary. There are three types of assets that can be affected by fire sales: equities, corporate debt securities, and asset and mortgage-backed securities. Each has a different value of market depth.

Calibration of the parameters is made difficult by the paucity of empirical analyses that reveal the price impact for a given volume of assets sold in fire sales. Our calibration is guided in part by Mitchell *et al* (2007), who consider a fire sale of US convertible bonds by hedge funds in 2005. They estimate that 5% of the outstanding stock of US convertible bonds were sold at a maximum price discount of 2.7%. Similarly, Coval and Stafford (2007) analyse the price impact of fire sales involving US equity mutual funds. They find an average price impact of 2.2% for the fire sales they identify. Pulvino (1998) focuses on fire sales of aircraft and finds larger price impacts for these assets. He also finds that the price impact varies when the depth of the market fluctuates. However, none of this information is sufficient for precise calibration, since it is not possible to make a direct comparison of the size of the fire sale in relation to the overall market in the study and the potential size in the case of any liquidation of UK banks' assets.

Therefore, the calibration is guided both by this empirical evidence and a top-down judgement regarding the plausible impact of a fire sale on capital.[18] The calibration for θ is based on the results presented in Mitchell *et al* (2007). Given θ, a value of market depth M_j is chosen for each of the asset types so that when the UK bank with the largest holdings of an asset class in its trading portfolio and AFS assets sells all these assets, it generates prices falls of 2% for equities, 4% for corporate debt, and 5% for asset and mortgage-backed securities.

2.5.2 Network model

When a bank defaults, counterparty credit losses incurred by other banks are determined using a network model. A matrix of interbank exposures for the major UK banks, along with some smaller UK institutions and a selection of large complex financial institutions (LCFIs) is built using reported large exposure data where available. Since we also have information on total interbank asset and liability positions, we then use maximum entropy techniques to fill in

[18] The impact is likely to be stronger when the financial system is under stress and markets are less deep (Pulvino (1998)).

missing gaps in the network, ensuring that none of the estimated entries exceed the reporting threshold for large exposures.[19] If any interbank assets or liabilities are unallocated following this procedure, we assume that they are associated with a residual sector which cannot default. Once constructed, the estimated exposure matrix remains static over the forecasting horizon. To clear the network following the default of one or more institutions, we use the Eisenberg and Noe (2001) algorithm. This both determines contagious defaults and returns counterparty credit losses for each institution.

2.5.3 Feedback loop

After accounting for counterparty credit losses and mark-to-market losses on AFS assets, we update the danger zone scores for banks that survived initially (see Figure 2). In the event of another bank breaching the 35-point threshold, we iterate around the network and asset-side feedback mechanism again. If not, we update all balance sheets to account for counterparty credit losses. However, we assume that asset prices recover to pre-feedback levels, so mark-to-market losses are not carried forward. This reflects the idea that, once a crisis has passed, asset prices are likely to return to their fundamental values fairly quickly. A more gradual price adjustment process would impose higher systemic costs on the banking system, and we plan to allow for this in future work.

2.6 Reinvestment

Rules for adjusting balance sheets to account for profits and losses are necessary in a multi-period setting. As noted above, post-tax, post-dividend profits (or losses) are assumed to increase (or erode) Tier 1 capital. On the asset side, credit losses are simply booked against the relevant exposure for the loss. But other profit and loss items cannot be linked so directly to particular balance sheet lines. Therefore, to rebalance the balance sheet, we adopt a set of mechanical reinvestment rules.[20] If operating income (which includes net interest income, non-interest income and trading income) exceeds operating expenses then, at the point of rebalancing, liabilities plus capital will exceed assets, and banks reinvest their surplus funds according to the following rules:

[19] The techniques adopted are similar to those discussed by Wells (2004), Elsinger *et al* (2006b) and OeNB (2006).
[20] Rules can be respecified in policy experiments, for example to assess the impact of targeting leverage, or of raising capital.

Rule (i): *Banks have a bank-specific 'target' Tier 1 capital ratio which they aim to meet when investing their funds.* (They are not permitted to buy back equity to meet their target.)

Rule (ii): *Subject to rule (i), banks invest in assets in proportion to their shares on the bank's initial balance sheet (so mortgage banks will, ceteris paribus, invest in mortgage assets rather than trading assets).*

Rule (iii): *Rule (i) determines total assets after reinvestment and hence the amount of new liabilities which need to be raised. These net new liabilities are allocated in proportion to their shares on the bank's initial balance sheet.*

In the current version of RAMSI, defensive actions in response to declines in capital are very limited. In the case when a bank's operating expenses exceed its operating income (so that assets exceed liabilities plus capital at the point of rebalancing), we assume that the bank is unable to disinvest or raise capital. Rather, it raises new liabilities according to rule (iii). The reinvestment rule therefore has the benefit of demonstrating transparently the implications when no mitigating actions are taken in the face of losses. But it is not necessarily realistic – for example, an alternative specification would allow banks to disinvest when making losses; this would reduce the likelihood of the bank suffering a liquidity crisis, but would introduce a further channel of macroeconomic feedbacks.

The primacy of the Tier 1 capital ratio rule is justifiable first, because five of the banks in our sample (Barclays, Bradford & Bingley, Halifax Bank of Scotland, HSBC and Royal Bank of Scotland) publish a Tier 1 capital ratio target; and second, because the mean ratio of capital to risk-weighted assets for the major UK banks was relatively stable in recent years (up to 2007) and institution-specific standard deviations of this ratio were low. For banks which have not published target capital ratios, we assume that they target a capital ratio equal to their end-2007 number.

We are motivated to choose 'neutral' assumptions regarding portfolio allocation and the second and third rules are based on the presumption that initial balance sheets represent desirable equilibrium outcomes which banks seek to preserve in the face of changes in size. Drastic changes in portfolio are typically associated with a change in the bank's business model – within a given business model, the rules seem reasonable, especially over the three-year horizon considered in this paper.

The portfolio allocation rules are not entirely neutral, however. The liability rule precludes banks from responding to changes in funding costs. And on the asset side, our assumed rule may understate risk because it precludes the possibility that banks may skew their reinvestment towards areas in which they have recently been most profitable. Following positive macroeconomic outcomes, risky assets tend to generate the most profits and increase most in value. So risks would accumulate more quickly were we to employ an alternative reinvestment rule in which banks reinvested profits in proportion to the nominal value of assets held on the balance sheet in the most recent period (rather than the initial period in our rule). We intend to conduct further validation to guide such choices.

There is no leverage target, so our reinvestment rules allow leverage to be determined according to developments elsewhere in RAMSI. As pointed out by Adrian and Shin (2008), leverage may be *procyclical* when positive macroeconomic outcomes lead to a decline in the measured riskiness of banks' existing assets (a decline in VaR or a fall in Basel II risk weights). Such procyclicality will be built into RAMSI when we introduce endogenous Basel II risk weights which adjust to changes in PDs. Conversely, if banks choose to purchase relatively risky assets (with high risk weights), then leverage rises relatively *less*, since in order to achieve their Tier 1 capital ratio targets, banks can purchase fewer assets compared with the case in which they purchase assets with lower or zero risk weights, such as government bonds.

3 Simulations

We use data up to 2007 Q4 (so that all balance sheet information is on the basis of end-2007 data) and run 500 simulations on a three-year forecast horizon stretching to the end of 2010. The BVAR is currently the only source of exogenous randomness in the stochastic simulations; each simulation is thus driven by a sequence of macroeconomic shocks drawn from a multivariate normal distribution.[21] It should be emphasised that the results are illustrative, reflecting model properties in this preliminary version rather than being the authors' view of the likely impact on the banks in question.

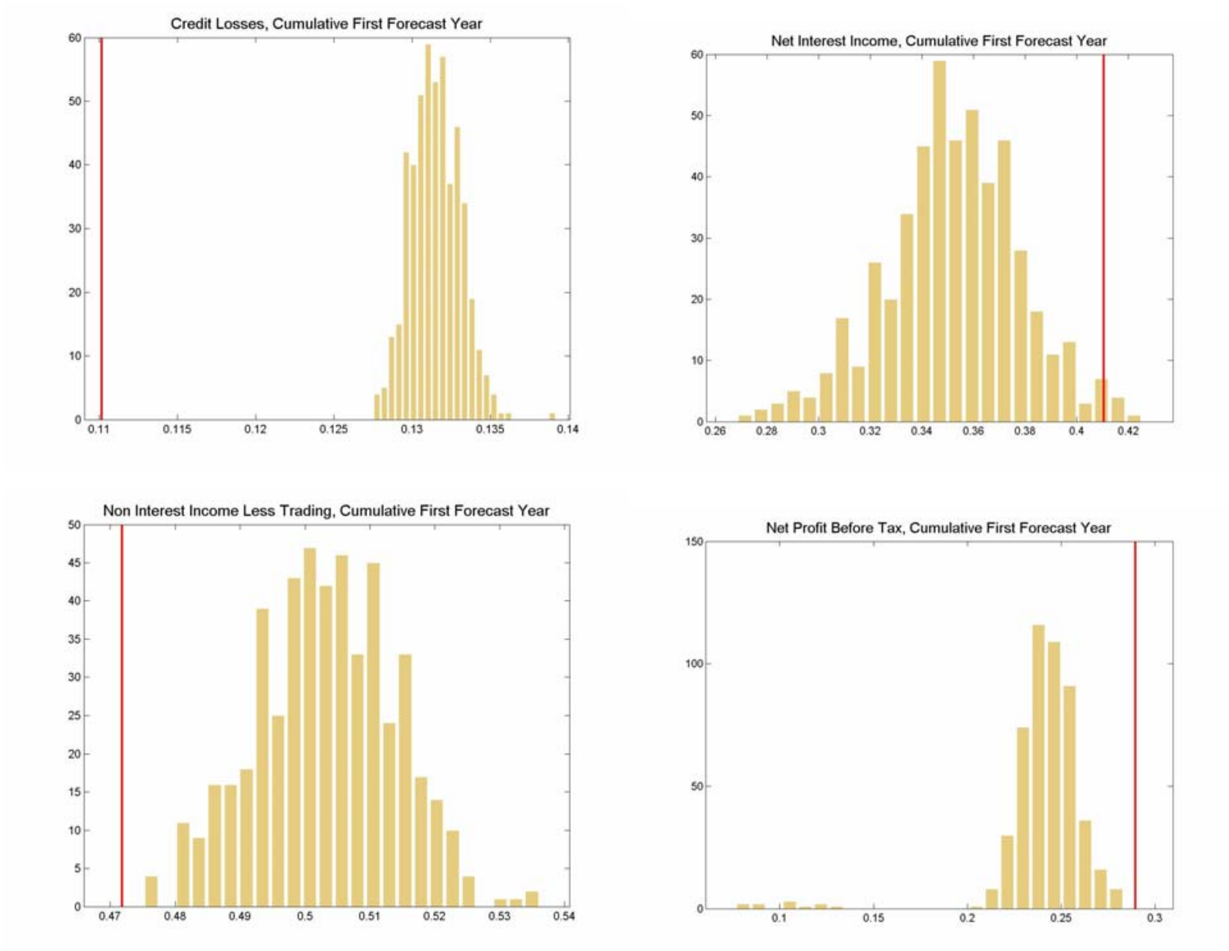
[21] In other words, we draw 500 realisations of the macroeconomic risk factors in the first quarter. In subsequent periods, we draw a single set of macroeconomic risk factors for each of the 500 draws.

3.1 Aggregate results

Throughout this section, we discuss results for the UK banking system in aggregate. Since individual banks' balance sheets are at the core of RAMSI, the model produces a rich set of information and may also be used both to obtain baseline projections for specific institutions and to analyse their performance under stress. Such information can be used to assess the vulnerability of particular institutions to different risks and may thus feed into the institution-specific risk assessment work undertaken by regulators and central banks.

Chart 2 shows the simulated distributions of some key profit and loss items. For each variable, we calculate aggregate cumulative figures for the first year by adding over banks and quarters, and normalise by aggregate 2007 ('beginning of period') capital. The vertical line represents the corresponding figures from the 2007 published accounts, normalised by 2006 capital levels.

Chart 2: Simulated distributions for profit and loss items (per cent of aggregate 2007 capital)



The top left-hand panel shows that credit risk is projected to increase in 2008, reflecting a worsening of the macroeconomic outlook. However, since our credit risk model abstracts from portfolio concentrations (see Section 2.3.1), we arguably underestimate the variance of the credit risk loss distribution. Net interest income is projected to be weaker than 2007, reflecting contractual frictions that prevent banks from instantaneously passing on higher funding costs to their borrowers. The variance of net interest income may be unrealistically high as the model does not incorporate hedging of interest rate risk.[22] Non-interest income (bottom left-hand panel) remains high, with a median projection above the reported 2007 level; this variable is procyclical but adjusts relatively slowly to macroeconomic changes. The net impact on banks' profitability is summarised in the net profit chart (bottom right-hand panel). Profits were projected to be weaker than in 2007, and there is some evidence of bimodality, insofar as there are a number of observations in the extreme tail of the distribution, which are typically associated with one or more banks defaulting.

3.2 Dissecting the tail: the role of funding liquidity and contagion

The crisis afflicting banks in the UK and internationally has illustrated the importance of funding liquidity risk. By their nature, the aggregate cumulative distributions in Chart 2 mask bank-by-bank heterogeneity. In bad draws, some banks incur large losses in some quarters/scenarios, which can erode those banks' Tier 1 capital ratios thereby increasing their danger zone points score on that indicator. With some banks scoring points on the liquidity indicators as well, the increased solvency concerns can, in extreme cases, be sufficient for a bank's score to reach 35 points, leading to the closure of short-term unsecured funding markets to that institution and its default. Note that the introduction of funding liquidity risk into the framework is critical here. Looking at capital alone, the defaulting banks remain above the 4% regulatory minimum. But a combination of relatively mild solvency concerns, a weak liquidity position and elevated market interbank spreads is sufficient for wholesale depositors to withdraw funding.

The crosses in Figure 6 show danger zones scores for a selected defaulting bank. The bank fails because it scores points on a range of the indicators, including the Tier 1 capital ratio indicator. But its weak liquidity position, captured in the second and third indicators, contributes to its failure. As such, it is clear that the inclusion of danger zones into the framework makes banks

[22] Banks can be penalised under the second pillar of Basel II for not hedging interest rate risk in their banking book.

more vulnerable. The results accord with reality in the sense that funding liquidity crises are triggered by a mixture of factors and can occur even if the bank is perceived to be solvent.

Contributing to bank heterogeneity are bank-specific funding spreads that depend on bank ratings. A bank is more likely to be downgraded as its profitability declines. This serves to raise its funding costs, hurting profits further and making the bank more vulnerable to subsequent default. We observe this feedback relationship in Chart 3. This shows two distributions for bank rating changes at the end of the forecast horizon or at the point of default, relative to the initial rating. The total number of observations is therefore 500 simulations multiplied by 10 banks. The lighter distribution is for scenarios in which the bank does not default and the darker distribution is for scenarios in which the bank defaults. As we expect, the defaulting bank-scenarios distribution has more of its mass at lower rating changes. It also includes the only cases in which there are two-notch downgrades.

Figure 6: Danger zone scores for a defaulting bank

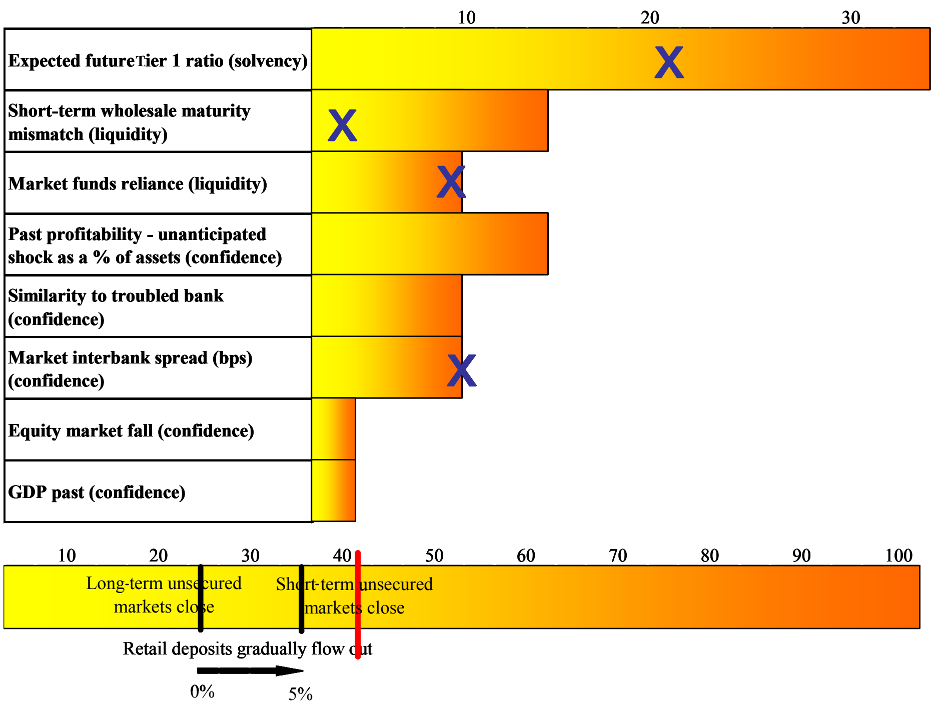
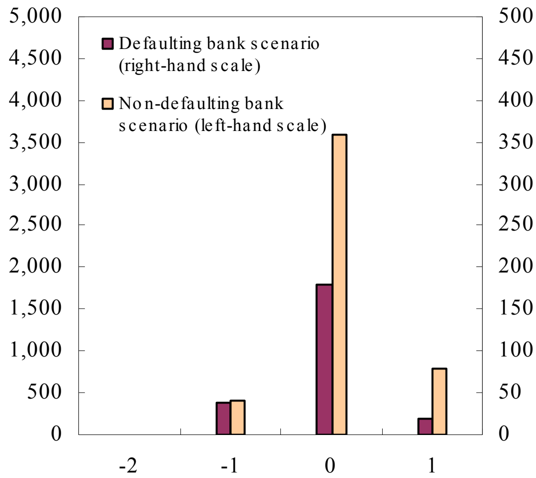


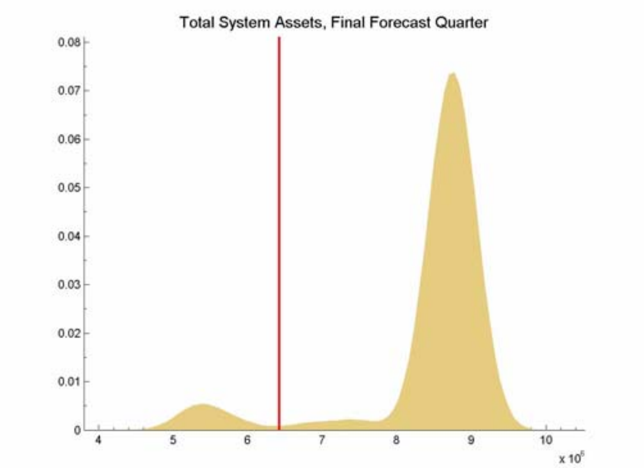
Chart 3: Rating distribution – cumulative change

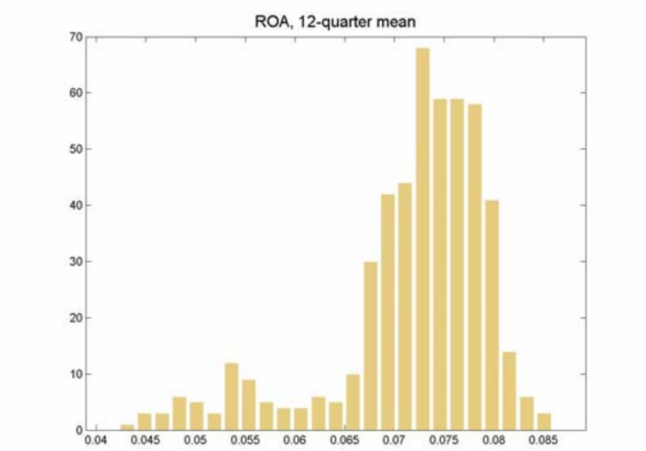


Note: The bars represent the cumulative changes in ratings (Q12 relative to initial) for each bank in each scenario. The lighter bars represent ratings for non-defaulting bank scenarios; darker bars for defaulting bank scenarios.

Chart 4 shows the distribution of total assets in the last quarter of the simulation and the average aggregate return on assets (RoA) over the whole horizon. These charts highlight the role of contagion in RAMSI. The distributions are bimodal, with a main peak associated with a healthy banking sector and a considerably smaller second peak in the left tail.[23] This is a direct consequence of bankruptcy costs and, in particular, network and asset-side liquidity feedbacks: since fundamental defaults can generate contagion, beyond a certain threshold 'extreme' negative outcomes become relatively more likely than 'moderate' negative outcomes. This result captures a phenomenon that is commonly perceived as a key feature of financial risk.

Chart 4: Total system assets – final quarter





[23] The bimodality is qualitatively robust and, we believe, crucial feature of the model. See Alessandri *et al* (2009) for more discussion of this bimodality.

The extent to which there is contagion in simulations in the left-hand tail is highlighted by the evolution of the danger zone points. For example, Table 4 presents the build-up of points for two other banks following the failure of the bank shown in Figure 6. As already discussed, this bank (Bank 1) defaults in a fundamental sense because it receives a danger zone score greater than 35. Prior to the failure of Bank 1, Bank 2 only has a danger zone score of 26.5. But it is perceived to be so similar to Bank 1 that it is tipped into default by this pure confidence effect. Contagion then extends to Bank 3. It too suffers because of its perceived similarity to the failed banks. But the failure of Bank 2 and the associated fire sale of its assets result in Bank 3 also incurring significant interbank and mark-to-market losses that eat into its capital – indeed, Bank 3 is the bank that suffers the greatest counterparty credit loss as a percentage of Tier 1 capital from the failure of Bank 2. Thus, both interbank losses and mark-to-market losses triggered by fire sales are important sources of contagion. This process clearly illustrates how funding liquidity problems at one bank can spread to other banks in tail simulations.

Table 4: Funding liquidity and contagion

	Bank 1	**Bank 2**		**Bank 3**		
	Initial	*Initial*	*After 1 default*	*Initial*	*After 1 default*	*After 2 defaults*
Expected future Tier 1 ratio	20.5	0	0	0	0	2
Short-term wholesale maturity mismatch	2	13	13	8	8	8
Market funds reliance	9	3.5	3.5	8	8	8
Past profitability	0	0	0	0	0	0
Similarity to troubled bank	0	0	9	0	7	10
Market interbank spread	10	10	10	10	10	10
Equity market fall	0	0	0	0	0	0
GDP past	0	0	0	0	0	0
Total	**41.5**	**26.5**	**35.5**	**26**	**33**	**38**

4 Policy applications

The ultimate goal for RAMSI is to provide a quantitative analytical framework for risk assessment work. To be successful, the model must provide a well-grounded narrative of how potential risks may play out. And in order to be useful for external communication, it needs to use metrics that are familiar to supervisors and risk managers. This section assesses some channels through which improvements should transpire, and highlights some further issues in using RAMSI for policy analysis.

Generation of aggregate and bank specific fan charts for a wide variety of financial variables (losses, lending, credit spreads etc). In producing fan charts there is a trade-off. On the one hand, there are benefits from improving the accuracy of fan charts by including additional sources of randomness to that arising from the BVAR, e.g. from the PD equations and liquidity risk. On the other, increasing the number of sources of randomness greatly increases model run times and breaks the direct mapping from macroeconomic scenarios to outcomes, so reducing the clarity of storytelling.

Testing the stability of the banking system under stress scenarios. RAMSI provides a framework for gauging the relative importance of risks and for assessing how they may play out. RAMSI will be of particular use in providing model-based estimates of the impact of risk scenarios, such as those highlighted in the Bank of England's *Financial Stability Report.* Relative to traditional stress tests, RAMSI integrates a wider range of channels through which shocks could propagate and takes account of the contagion that may occur through interbank exposures, asset fire sales, funding liquidity and macroeconomic feedbacks. Assessment of second-round effects has been identified by Haldane (2009) as an important area for development of stress testing in the financial system.

Assessing sources of risk to banks. RAMSI will provide the relative contributions to overall risk of the various modules (credit risk, market risk, funding risk, interest income risk and other risks). In particular, RAMSI may be used to assess the contribution of systemic feedbacks to overall risk.

Intermediate outputs. A number of RAMSI's outputs may be useful analytical tools, even when used in isolation of the rest of RAMSI. Examples include balance sheets, the credit loss model, the net interest income model, the ratings model, and the danger zone scores for funding liquidity crises.

Policy experiments. RAMSI can be used for counterfactual experiments in which regulatory changes could affect systemic risk (see for example Goodhart (2008)). For example, it could be used to assess the extent to which varying capital and liquidity buffers can reduce systemic risks. And, once Basel II dynamic risk weights which adjust to changes in credit risk are introduced, a certain degree of procyclicality will be built into the baseline of RAMSI and the model could then be used to examine the effects of varying capital requirements across the cycle. In any experiment of this type, the impact on risk and profitability could be observed on either a bank-by-bank or an aggregate basis.

Recapitalisation. RAMSI could be used to calibrate the extent to which the recent recapitalisation of the UK banking system reduces systemic risk.

5 Conclusion and further work

This paper incorporates funding liquidity risk into a quantitative model of systemic stability. By applying the model to the UK banking system based on the balance sheet vulnerabilities that existed at the end of 2007, we demonstrate how rising funding costs and liquidity concerns can amplify other sources of risk. The unified modelling approach sheds light on risks arising throughout banks' balance sheets. It also demonstrates how defaulting financial institutions may cause contagion by triggering default cascades through the interbank market; selling assets at fire sale prices; and through undermining confidence in other banks.

We intend to develop the model in a number of areas. A substantial area for further work is to analyse banks' cash-flow constraints and consider how defensive actions in the face of funding stress may affect the rest of the financial system and the wider macroeconomy. Another key challenge is to incorporate feedbacks from the banking sector to the real economy. In principle, this could be done by adding an aggregate lending measure to the BVAR and then treating changes in banks' supply of credit at a given point in time (in terms of either quantities or prices) as lending shocks for the subsequent period. Needless to say, such a mechanism would need to be carefully designed in order to preserve the internal consistency of the framework. Finally, we intend to introduce more sources of randomness in the model beyond the BVAR, for example in PDs – such developments would clearly add to the computational complexity of RAMSI, but would improve the realism of the various fan chart summaries of outcomes. Ultimately, the future development of the RAMSI framework will be determined to a large degree by the aspects of the model that are found to be most useful in enhancing understanding of, and communicating concerns about, financial vulnerabilities. Our hope is that the analytical framework RAMSI provides becomes central to the analysis of systemic risk in the United Kingdom, and perhaps in some other countries as well.

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