Towards a Framework for Quantifying Systemic Stability*

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This paper describes a prototype quantitative framework for gauging systemic risk which explicitly characterizes banks' balance sheets and allows for macro credit risk, interest income risk, market risk, network interactions, and asset-side feedback effects. In presenting our results, we focus on projections for systemwide banking assets in the United Kingdom, considering both unconditional distributions and stress scenarios. We show how a combination of extreme credit and trading losses can

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precipitate fundamental defaults and trigger contagious default associated with network effects and fire sales of distressed assets. Despite the joint normality of all risk factors, the model generates a bimodal asset distribution.

JEL Codes: G01, G21, G32.

1. Introduction

Whilst central banks have long used models to guide monetary policy decisions, models of financial stability and systemic risk are much less well developed. The lack of an adequate analytical framework has meant that the financial stability risk-assessment work of central banks is often couched in more qualitative terms. As a result, the analyses presented in some financial stability reports all too often resemble a laundry list of things that could go wrong and, more recently, have gone wrong.

This paper describes work in progress at the Bank of England to develop a quantitative framework to help guide and sharpen macroprudential analysis. As with macroeconomic models in the monetary policy context, a quantitative approach provides a means of filtering news and assessing interrelationships between variables. It can provide insights to policymakers on the probability and potential impact of major threats to the financial system and can help them communicate their views clearly. In times of crisis, it can also be used as a guide to assess the vulnerability and systemic importance of individual institutions. For example, an approach of this sort could be used to shed light on whether the failure of an institution like Bear Stearns would pose a greater threat to systemic stability than that of Lehman Brothers.

The Risk Assessment Model for Systemic Institutions (RAMSI for short) focuses on the health of the UK banking system, with particular emphasis on risks over and above those priced and managed by financial institutions themselves. In the current version of RAMSI, the externalities that generate such "systemic risk" stem from the connectivity of bank balance sheets via interbank exposures and the interaction between balance sheets and asset prices. Default cascades can arise as a result of the direct interlinkages of claims and obligations in the financial network and may be reinforced by asset-price spirals, particularly when the market for key system assets is illiquid.

The analytical foundation of our approach stems from recent theoretical work on modeling systemic financial crises. Allen and Gale (2000) explore the spread of contagion in a banking network and Cifuentes, Ferrucci, and Shin (2005) examine how default across the network can be amplified by asset-price effects. Gai and Kapadia (2008) examine the nonlinearities implied by both these externalities and suggest that modern banking systems may be robust-yet-fragile in nature. The greater connectivity of financial networks enhances risk sharing and lowers the probability of a crisis. But direct and indirect balance-sheet interdependencies mean that the impact of crises, when they occur, can be much greater than in less-connected systems. This result is reinforced by Gai et al. (2008), who suggest that financial innovation and greater macroeconomic stability may have intensified the robust-yet-fragile nature of modern banking systems.[1]

In what follows, we show how models of the macro economy and banks' balance sheets can be brought together and integrated with models of the interbank network and asset-side feedbacks to generate illustrative forecast distributions for institution-specific and systemwide losses and banking assets over arbitrary horizons. Although we impose jointly normal shocks, we show that the network and asset-price feedback effects induce nonlinearities. These make our distributions bimodal in character, with a main peak associated with a healthy banking sector and a considerably smaller second peak in the extreme tail associated with outbreaks of contagious default.

At root, bankruptcy costs, which erode the assets of defaulting banks in our model, are the key source of this bimodality because they create a large, discrete loss at the point of default. But network effects and adverse asset-price feedbacks have a critical role: following the default of one bank, other banks may be tipped into default due to counterparty credit losses and mark-to-market write-downs on some of their assets. If default occurs, and especially if contagion breaks out, the cumulative bankruptcy costs therefore yield a systemwide outcome that is discretely and considerably worse than if the initial default is just avoided. Our model thus generates bimodal

[1]See Rajan (2005), Tucker (2005), and Gieve (2006) for policymaker perspectives on this issue.

distributions in a context where banks do not optimize and there is no strategic interaction—this contrasts with existing literature (e.g., Morris and Shin 1999), which focuses on how bimodal distributions may arise in illiquid markets due to strategic interaction amongst traders with heterogeneous information sets.

Comparing Lehman Brothers with banks that have just avoided default serves to highlight how this bimodality may manifest itself in reality. Upon the failure of Lehman Brothers in September 2008, its creditors are likely to have incurred a range of direct expenses such as legal, accounting, and trustee fees.[2] Over time, financial institutions may also suffer losses from the cheap (fire-sale) liquidation of assets, which may be severe when the wider banking industry is also in distress (Shleifer and Vishny 1992), and can represent a real cost if the cheap sale is due, for example, to a disruption to established bank-borrower relationships. On their own, these losses represent a discrete, deadweight loss to the system which would not have been incurred if Lehman Brothers had survived. But it was the contagion from the failure of Lehman Brothers that caused a major amplification in systemwide distress and arguably moved the entire banking system from a precarious, but possibly sustainable, state to a full-blown crisis.[3]

A key value of RAMSI is its potential as a policy tool for risk-assessment and stress-testing exercises. For example, it can yield point estimates for losses and future assets if paths for all macroeconomic variables are specified ex ante. Alternatively, it can be used to generate conditional distributions by perturbing parameters and/or a set of macroeconomic and other variables in any period. In this paper, we illustrate the latter type of stress test by examining the conditional systemwide asset distributions that are obtained from an illustrative scenario which combines adverse market sentiment with distress in the U.S. household and global corporate sectors.

[2]Bris, Welch, and Zhu (2006) find that these costs are considerable for a wide sample of corporate bankruptcies in the United States, sometimes amounting to up to 20 percent of assets. Meanwhile, for the banking sector, James (1991) estimates direct bankruptcy costs to be equivalent to approximately 10 percent of the failed bank's assets.

[3]For a more detailed discussion of the financial crisis and the events following the failure of Lehman Brothers, see the Bank of England *Financial Stability Report* (2008).

Central banks and regulators are increasingly seeking to use formal models to support their financial stability work, and various modeling approaches have emerged in recent years. Some authors (e.g., Goodhart, Sunirand, and Tsomocos 2006) have attempted to model systemic risk in a general equilibrium framework, but these models are highly stylized and extremely difficult to operationalize. A much more common alternative is to rely on a modular approach. In this case, a macroeconomic model is combined with models that describe how the risk profiles—and notably the default probabilities—of key financial institutions respond to changes in macroeconomic conditions.

The link between macroeconomic factors and default probabilities can be formalized in two ways (see Sorge and Virolainen 2006). One possibility is to rely on an option-pricing framework and extract risk from observed security prices. This "asset-pricing" approach can be applied to individual banks (Elsinger, Lehar, and Summer 2006a; Segoviano and Padilla 2006; Frisell et al. 2007) or indeed entire sectors of the economy (Gray, Merton, and Bodie 2007). These models typically use publicly available, high-frequency data, can track changes in market perceptions of banks' risk profiles in a timely fashion, and capture the market's view on the risks in the system. However, they rely on strong assumptions on the completeness and efficiency of the markets in which the securities are traded. And, as market prices may embed the possibility of official support, asset-pricing models may be unable to identify the extent to which intervention may help to mitigate systemic risks (for a formalization of this argument, see Birchler and Facchinetti 2007).

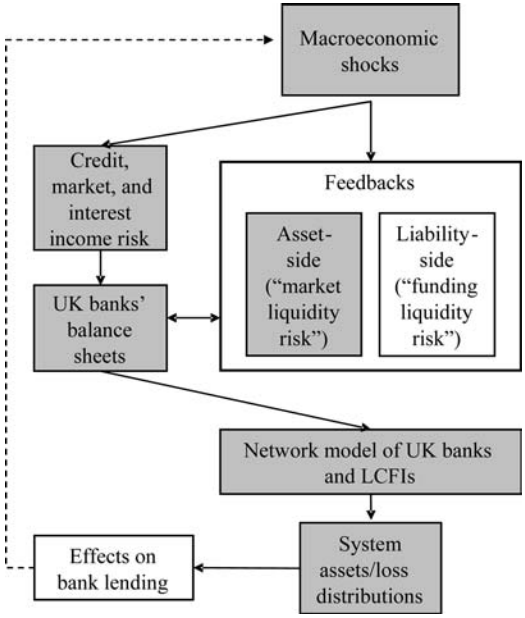
A second option, pursued in this paper, is to use balance-sheet data and separately estimate the performance of the bank's exposures. Although they are not microfounded and typically rely on behavioral "rules of thumb," these "balance-sheet" models offer a flexible and operational means of capturing a wide range of risks and transmission channels. And, compared with the asset-pricing approach, the transparency of the transmission channels allows for a more articulated analysis and interpretation of the outputs of stress-testing exercises. Because of this "story-telling" ability, many central banks use this type of framework as an input to their financial stability analysis (Borio and Drehmann 2009; Foglia 2009). But existing models tend to focus solely on credit risk.

In terms of contagion, some central banks model counterparty credit risk through an interbank network (see Upper 2007 for a comprehensive survey). Most of these models focus on the exogenous failure of particular institutions, though there is an increasing tendency, especially within the asset-pricing approach, to integrate aggregate shocks into the framework (see, e.g., Elsinger, Lehar, and Summer 2006a or Frisell et al. 2007).

The framework developed by the Oesterreichische Nationalbank (2006) for the Austrian banking system (see also Elsinger, Lehar, and Summer 2006b) is most closely related to our work in that it takes a balance-sheet approach and integrates a network model with models of credit and market risk to evaluate the probability of bank default. Our paper builds on their approach, developing a model of net interest income and capturing the feedback effects associated with the asset side of bank balance sheets. Recent events suggest that these feedback effects are crucial to systemic risk in modern banking systems. Further, whilst the Austrian model is limited to a one-quarter forecasting horizon, restricting its ability to assess the full impact of slow-burn risks to the financial system, our model is dynamic and allows for arbitrary horizons. The duration of the ongoing crisis has emphasized the importance of being able to make projections over several years.

Our paper is intended to provide an illustrative framework for how systemic stability in a modern banking system might begin to be quantified, and it is very much work in progress. As such, the calibration and estimation adopted in the prototype version of the model described in this paper is deliberately broad-brush in nature to emphasize the qualitative results of the model. More importantly, several key channels are excluded in this initial version. These include funding liquidity risk, off-balance-sheet risks, and feedbacks from the banking sector to the macro economy, all of which have been central to the ongoing financial turmoil and represent the focus of our current model development efforts. Therefore, the numerical results should not be construed to be an accurate measure of systemic risk in the UK banking system. And though some of our results may shed qualitative light on recent events, the model keys off end-2005 data and should not be viewed as quantifying any aspect of the ongoing financial crisis.

Figure 1. Suite of Models



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 systemwide distributions obtained from the stochastic simulation of risk factors and illustrates the possibility of contagious default associated with network effects and asset fire sales. Section 4 presents the outcome of our illustrative stress scenario, and a final section concludes with suggestions for future research.

2. The Modeling Framework

Figure 1 illustrates the structure of RAMSI and the mapping from shocks to systemic risk.[4] The transmission dynamics hinge crucially on two factors—the nature and scale of shocks and the structural

[4]We use the word "shocks" to refer to unexpected changes in macroeconomic variables. No econometric identification strategy is pursued in this paper, so our shocks are generic random innovations to the macroeconomic data-generating process (see section 3).

characteristics of the financial system, such as the heterogeneity of balance sheets, the connectivity of the interbank network, and so on. In such an environment, balance-sheet interdependencies and asset-price feedbacks make for complex, nonlinear behavior. RAMSI can produce asset distributions for the banking system by linking together the shaded modules presented in figure 1—the unshaded modules are discussed briefly in the conclusion but are left for future work. In what follows, we discuss the overall modeling strategy in RAMSI before briefly discussing each of its components.

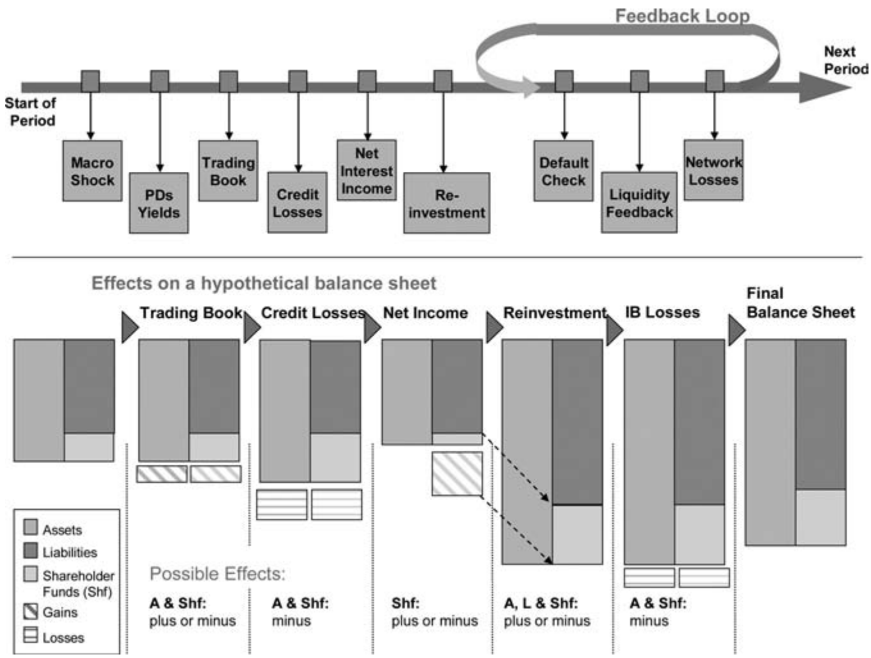
2.1 Overview and Sequencing

The model can be run over an arbitrary forecasting horizon as it takes account of the reinvestment of profits between quarters. In this paper, we adopt a time frame of twelve quarters. A three-year horizon seems appropriate given the duration of business and credit cycles—in particular, it takes time for some adverse shocks to be reflected in credit losses (Bunn, Cunningham, and Drehmann 2005; De Nederlandsche Bank 2006). And central banks often use a three-year horizon when stress testing their financial systems (see, e.g., Hagen et al. 2005, Bank of England 2007, and Sveriges Riksbank 2007).

The sequence of events is illustrated in figure 2. Macroeconomic risk factors for each quarter are generated using a simple two-country macroeconomic model estimated for the United Kingdom and the United States. These risk factors are used to derive both a yield curve and probabilities of default on UK banks' household and non-financial corporate credit exposures. For each combination of risk factors, we model three first-round effects on each of ten major UK banks.[5] First, we model gains/losses on net trading and other financial assets held by the banks. Second, we account for credit losses. And third, we capture the effects on net interest income. For now,

[5]Membership of the major UK banks group is based on the provision of customer services in the United Kingdom, regardless of country of ownership. The following financial groups, in alphabetical order, were members at the end of 2007 and are included in the model: Alliance & Leicester, Banco Santander, Barclays, Bradford & Bingley, Halifax Bank of Scotland, HSBC, Lloyds TSB, Nationwide, Northern Rock, and Royal Bank of Scotland.

Figure 2. Model Timeline



we do not model the evolution of other income and costs, though these can be incorporated into the framework.

After computing the first-round impact on each bank, we update the balance sheets of profitable banks using a rule of thumb for reinvestment behavior. Specifically, we suppose that banks try to maintain their initial leverage and tier 1 capital ratios and invest in assets in proportion to their shares on their initial balance sheet. For banks that incur losses, however, we apply a "threshold rule" based on the Basel I regulatory minimum for tier 1 capital to determine whether any of them default. If no bank fails, the simulation for the quarter ends and we immediately proceed to model the effects of the following quarter's risk factors on the banking system.

When a bank fails, it incurs a bankruptcy cost. A fraction of its assets are lost, reducing the amount available to its creditors. The bank then defaults on obligations that it cannot fulfill in the inter-bank network, imposing counterparty credit losses on other banks in the system. The trading and other financial assets of failed banks are sold in a secondary asset market, creating asset-side feedbacks which cause other banks to suffer temporary mark-to-market losses on these asset classes. We account for both counterparty credit losses and mark-to-market losses on net trading and other financial assets before reapplying the threshold default rule to banks which initially survived.[6] If any of these banks now default, we iterate around the network and asset-side feedback mechanism again. If not, we proceed to the next quarter after rebalancing all balance sheets to account for counterparty credit losses. We assume, however, that mark-to-market losses are not carried forward. In other words, the price of the fire-sale assets recovers to its (fundamental) pre-feedback level.

Throughout the paper, we assume that there are no regulatory or other policy interventions, aside from any short-term interest rate response embedded in and endogenous to the macroeconomic model. This is partly because modeling policy reaction to extreme events is inherently difficult, especially given that there is no single, standard response to financial crises. But we also feel that it is particularly interesting from a practical perspective to assess how the financial system would fare *without* any policy response, as it allows judgments to be drawn on the potential benefits and costs of intervening.

2.2 Macroeconomic Model

The macroeconomic risk factors are simulated using a two-country version of the global VAR (GVAR) model of Pesaran, Schuermann, and Weiner (2004). We treat the United Kingdom as a small open economy and take the United States to represent the rest of the world. The model is estimated quarterly over 1979:Q1–2005:Q4 and has the following reduced form:

$$x_t^{uk} = a_0^{uk} + a_1^{uk} t + \Phi_1^{uk} x_{t-1}^{uk} + \Phi_2^{uk} x_{t-2}^{uk} + \Lambda_0 x_t^{us} + \Lambda_1 x_{t-1}^{us} + \epsilon_t^{uk}, \tag{1}$$

$$x_t^{us} = a_0^{us} + a_1^{us} t + \Phi_1^{us} x_{t-1}^{us} + \Phi_2^{us} x_{t-2}^{us} + \epsilon_t^{us}. \tag{2}$$

[6] These network and asset-side feedback effects are applied to the balance sheets of other banks *after* they have been updated to account for the reinvestment of any surplus (see figure 2). As such, network and asset-price externalities influence banks' balance sheets at the end of each quarter.

Variables and data are the same as in Dées et al. (2007). For the United Kingdom, these are real output (GDP), CPI inflation (CPI), real equity prices (EQP), an overnight nominal interest rate (SR), a twenty-year nominal interest rate (LR), and the sterling-dollar real exchange rate (EX). For the United States, the real exchange rate is replaced by the oil price (OIL). The GDP and CPI series are seasonally adjusted. Output, equity prices, and the exchange rate are modeled in logarithms. A zero bound is imposed on nominal interest rates. For simplicity, we approximate the yield curve by linearly interpolating the short- and long-term interest rates implied by the GVAR. This is the source of all risk-free rates used in the model.

2.3 First-Round Impact on Banks

2.3.1 Asset and Liability Classes on the Balance Sheet

We split balance sheets into fifteen asset and eight liability classes. Assets are divided into domestic and foreign exposures; for simplicity, we assume that exchange rate risk is fully hedged. Where possible, we also combine information from published accounts with confidential information provided by the ten UK banks in our sample to break down the total figures into five repricing buckets: zero to three months, three to six months, six to twelve months, one to five years, and greater than five years. Non-interest-bearing items are grouped separately. We then model the balance-sheet gains and losses and cash flows on each of these asset and liability classes. Table 1 summarizes this information.

Throughout this analysis, we simply take balance sheets as given—we do not model off-balance-sheet items such as commitments, or attempt to adjust for credit-risk transfer, securitization, hedging of interest rate risk, or other similar activities which are likely to mean that balance sheets will not fully reflect the risks to which banks are exposed. Clearly, a proper treatment of these issues is an important area for future work.

2.3.2 Trading-Book Gains and Losses

In the absence of formal top-down models of gains and losses on the trading book, we suppose that trading assets increase in value when the equity market is buoyant and interest rates are falling. The

Table 1. Asset and Liability Classes on the Balance Sheet and Associated Modeling

Assets[a]			
Asset Class	**Modeling of Losses/Gains**	**Modeling of Cash Flow**	**Risk Weight**
Trading and other financial assets[b]	Using trading-book equation	Risk-free rate + 15 bps[c]	50%
UK interbank unsecured[d]	Via network	Risk-free rate + 15 bps	35%
UK household secured (mortgage)	UK Mortgage PD*UK Mortgage LGD (17%)*Exposure	Coupon from net interest income model + 50 bps	35%
UK household unsecured	UK Unsecured PD*UK Unsecured LGD (100%)*Exposure	Coupon from net interest income model + 50 bps	75%
UK government	Assumed not to default	Risk-free rate	0%
UK PNFC	UK Corporate PD*UK Corporate LGD (84%)*Exposure	Coupon from net interest income model + 50 bps	100%
UK OFC	15 bps spread implied PD*UK OFC LGD (13%)*Exposure[e]	Risk-free rate + 15 bps	40%
UK other assets[f]	Assumed not to default	Risk-free rate	0%

[a] All footnotes referring to UK asset classes also apply to foreign asset classes.
[b] Includes trading portfolio assets (minus certificates of deposit), available-for-sale financial investments, and financial assets designated at fair value.
[c] At the short end, this is roughly in line with LIBOR prior to the recent financial crisis.
[d] Unsecured interbank loans + derivatives + certificates of deposit.
[e] 15 bps spread implied PD is equivalent to the PD implied by the average difference between the LIBOR in pre-crisis times and the short risk-free rate under the assumption that the spread entirely reflects credit risk.
[f] Includes reverse repos.

(continued)

Table 1. (Continued)

Assets			
Asset Class	**Modeling of Losses/Gains**	**Modeling of Cash Flow**	**Risk Weight**
Foreign interbank unsecured	Assumed not to default[g]	Risk-free rate + 15 bps	35%
Foreign household secured (mortgage)	US Mortgage PD*UK Mortgage LGD (17%)*Exposure	Coupon from net interest income model + 50 bps	35%
Foreign household unsecured	US Unsecured PD*UK Unsecured LGD (100%)*Exposure	Coupon from net interest income model + 50 bps	75%
Foreign government	Assumed not to default	Risk-free rate	2%
Foreign PNFC	US Corporate PD*UK Corporate LGD (84%)*Exposure	Coupon from net interest income model + 50 bps	100%
Foreign OFC	15 bps spread implied PD*UK OFC LGD (13%)*Exposure	Risk-free rate + 15 bps	40%
Foreign other assets	Assumed not to default	Risk-free rate	0%

Liabilities		
Liability Class	**Modeling of Losses/Gains**	**Modeling of Cash Flow**
Trading liabilities	Using trading-book equation	Risk-free rate + 15 bps
Unsecured interbank[h]	N/A	Risk-free rate + 15 bps
Household	N/A	Risk-free rate minus variable negative spread[i]
Government	N/A	Risk-free rate
PNFC	N/A	Risk-free rate minus variable negative spread[j]
OFC	N/A	Risk-free rate + 15 bps
Subordinated liabilities	N/A	Risk-free rate + 15 bps
Other liabilities[k]	N/A	Risk-free rate + 15 bps

[g] The only exception is if a foreign bank defaults in the network as a result of the failure of a UK bank. In this case, UK banks can suffer losses on foreign interbank assets.

[h] Unsecured interbank deposits + derivatives.

[i] The negative spread on household deposits is 200 bps in the 0–3 months repricing bucket, 150 bps in the 3–6 month bucket, 100 bps in the 6–9 month bucket, 50 bps in the 9–12 month bucket, and 0 bps at longer maturities.

[j] The negative spread on household deposits is 100 bps in the 0–3 months repricing bucket, 75 bps in the 3–6 month bucket, 50 bps in the 6–9 month bucket, 25 bps in the 9–12 month bucket, and 0 bps at longer maturities.

[k] Includes debt securities and repos.

reverse is assumed to hold for trading-book liabilities. Changes in the value of the trading book evolve according to a linear relationship for net trading assets, NTA.[7] Specifically,

$$\frac{NTA_t}{NTA_{t-1}} = 1 + \gamma_1(\Delta EQP_t - \Delta EQP^*) + \gamma_2 \Delta SR_t + \gamma_3 \Delta LR_t, \quad (3)$$

where ΔEQP^* is the historical mean return on equity over 1979:Q1–2005:Q4 and the right-hand-side macroeconomic variables are simple averages of UK and U.S. realizations. The use of net trading assets means that we are implicitly assuming that banks' liability positions are the exact reverse of their asset positions. In what follows, we take $\gamma_1 = 0.208$ and $\gamma_2 = \gamma_3 = -1.25$. Ceteris paribus, a 12 percent fall in equity prices relative to the trend growth rate or a 2-percentage-point rise in either short- or long-term interest rates causes a 2.5 percent decline in the value of net trading assets.

It is important to stress that the modeling and calibration of the trading book is intended to be illustrative. Indeed, the parameters in this prototype model have been deliberately chosen to ensure that fundamental defaults occur in some scenarios, thus allowing us to explore the feedback channels built into the framework. A more plausible model would break down banks' trading assets and liabilities into more granular classes (e.g., equities, bonds, etc.) and attempt to model each of these categories individually. In addition, it would allow for asymmetries and nonlinearities in trading gains and losses.

2.3.3 Credit Losses

Credit losses on household and corporate exposures are computed by multiplying an appropriate default probability (PD) for the asset class by a constant loss given default (LGD) to obtain a write-off rate.[8] With the exception of the PD for other financial companies, which is backed out from an assumed LIBOR spread (see table 1),

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[7]Net trading assets are taken to be trading and other financial assets, as defined in table 1, net of trading liabilities. Note that this exaggerates banks' true exposure to market movements, as it does not account for derivatives and other hedging activity.

[8]Most other asset classes are assumed not to default. See table 1 for full details.

PDs are estimated as linear functions of the macroeconomic outputs of the GVAR as follows:

$$L_t = \alpha + \beta_1 \Delta GDP_{t-1} + \beta_2 \Delta EQP_{t-1} + \beta_3 SRR_{t-1} + \varepsilon_t, \qquad (4)$$

where SRR_t is the short-term real interest rate and L_t is the quarterly log-odds transform of the default ratio for each of the following sectors in the United Kingdom and the United States: household secured (mortgages), household unsecured, and private nonfinancial corporate (PNFC). In specifying the equations, we impose $\beta_{1,2} < 0$ and $\beta_3 > 0$, deliberately ignoring any correlations that are at odds with our theoretical priors. The resulting models have R-squared coefficients between 5 percent and 30 percent. This simple specification may underestimate the volatility and persistence of actual PDs, but it allows us to capture some of the cyclicality of credit risk, and we consider it adequate given the focus of the paper.

We assume LGDs of 100 percent for unsecured household loans, 17 percent for mortgages, 84 percent for nonfinancial corporate loans, and 13 percent for financial corporate loans. The LGDs are assumed to be the same for domestic and foreign exposures. We choose these LGDs to allow us to match the average write-off rates observed over the available data sample (1993–2005 for corporates and 1997–2005 for households). The implied LGDs appear to be fairly high, but this is likely to reflect underrecording of defaults.[9]

At any given point in time, credit losses are calculated by simply multiplying (state-contingent) write-off rates by the relevant exposures (we assume that U.S. write-off rates apply to all foreign exposures). This calculation is underpinned by a fairly strong assumption—namely, that banks hold infinitely granular portfolios. It implies that realized credit losses are linear functions of the underlying PDs. In reality, portfolio concentration (or "lumpiness") is an

[9]Because of informal debt restructurings, recorded data on bankruptcies tend to underestimate the true scale of default, especially in relation to household unsecured debt. As a result, for some asset classes, even an LGD of 100 percent implies a write-off rate that is well below historical figures. In those cases, we scale up the measured PDs so that we can match observed write-off rates using LGDs which fall between 0 and 100 percent.

important driver of credit risk, and it is responsible for various well-documented stylized facts, including significant skewness in realized credit losses. Though we could introduce this ingredient in our framework (for instance, by using a Bernoulli mixture model), we sacrifice some realism to keep our analysis simple and maintain a transparent, direct link between macroeconomic risk factors and realized credit losses.

2.3.4 Net Interest Income

An important novelty of our framework is the modeling of endogenous interest income. 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' ability to reset coupons is constrained by the repricing structure of their balance sheets. Since assets and liabilities typically do not have matched repricing frequencies, these constraints generate significant income risk. And possible shifts in the yield curve intensify this risk.

In this paper, we use the risk-neutral asset pricing model of Drehmann, Sorensen, and Stringa (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:

$$EV(A_0) = \sum_{t=1}^{T} D_t C A_0 + D_T A_0, \tag{5}$$

where the discount factors are given by

$$D_t = \prod_{l=1}^{t} (1 + R_{l-1,l})^{-1}, \tag{6}$$

$$R_{l-1,l} = \frac{r_{l-1,l} + PD_{l-1,l} * LGD}{1 - PD_{l-1,l} * LGD}, \tag{7}$$

and $r_{l-1,l}$ and $PD_{l-1,l}$ represent, respectively, the forward risk-free interest rate and the expected default probability between time $l-1$

and l.[10] We can use equation (5) to calculate a "fair" time-zero coupon that guarantees that $EV(A_0) = A_0$:

$$C_0 = (1 - D_T) / \sum_{t=1}^{T} D_t. \tag{8}$$

Whenever the bank can update C (i.e., at time T, $2T, \ldots$), it will do so using (8), so that expected interest income covers expected losses and book and economic value coincide. Between 0 and T, though, interest rates and PDs may change, whereas the coupon is 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 what fraction of assets and liabilities 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.

Since we do not have a domestic-foreign split of liabilities, we use the UK yield curve to determine the appropriate risk-free rate for both domestic and foreign assets. Though clearly unrealistic, this avoids the severe distortion to net interest income that would arise if some assets were repriced on a different basis to corresponding liabilities. But it implies that foreign macroeconomic risk factors only affect PDs and hence the credit-risk component of the coupon.

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 additional profits derived by banks. In particular, for household and nonfinancial sector corporate assets, the model-implied coupon is increased by 50 basis points. For other parts of the balance sheet, including all of the liability side, we simply calibrate spreads to accord with reality. For example, we impose negative spreads on some retail and corporate deposits (if the negative spread implies a negative interest rate, the interest rate paid is assumed to be zero). Table 1 provides a detailed summary of the cash flows paid on assets and liabilities.

[10] The risk-free yield curve is known at the time of pricing; we assume that banks take future PDs to be equal to the most recent observation.

2.4 Reinvestment Behavior

As noted above, banks in RAMSI rely on a rule of thumb to update their balance sheets when they make profits.[11] Specifically, when shareholder funds grow, banks follow three distinct rules in increasing their liability base and investing extra resources:

(i) "Leverage" Target: When shareholder funds increase, a bank raises extra resources (liabilities) up to the point where the initial shareholder funds to liabilities ratio is restored.

(ii) "Tier 1 Ratio" Target: In investing the available cash (i.e., net profits plus, potentially, the increase in liabilities), banks aim to maintain or restore the initial ratio of shareholder funds to risk-weighted assets.

(iii) "Portfolio Composition" Rule: Subject to (ii), banks invest in assets in proportion to their shares on the bank's initial balance sheet (e.g., mortgage banks will, ceteris paribus, invest in mortgage assets rather than trading assets).

Note that banks may be unable to fully meet their targets at the start of each period. In particular, if they have suffered a series of losses and make another loss or only a small profit, they will be unable to restore their tier 1 capital ratio to its initial level. Therefore, accumulated losses may weaken banks' capital positions for several quarters.

The reinvestment assumptions are motivated by the presumption that the initial balance sheets represent desirable equilibrium outcomes which banks seek to preserve in the face of changes in size. Some empirical justification for leverage targeting is provided by Adrian and Shin (2008, figure 2.4), who find signs in the data which suggest that commercial banks target a fixed leverage ratio. Meanwhile, historical evidence from UK banks can be used to support capital-ratio targeting. In particular, over the 1997–2004 period, the mean ratio of capital to risk-weighted assets for the major UK banks has been relatively stable, and institution-specific standard

[11] We rule out equity buybacks in profitable states. If banks make losses, we assume that their shareholder funds are eroded but they are unable to disinvest or raise capital. Rather, they simply raise new liabilities. For simplicity, our analysis also currently ignores the balance-sheet effects of taxes and dividends.

deviations of this ratio have been low.[12] Support for the rule that banks grow their balance sheets in proportion to the initial composition of their portfolio is more difficult to defend over a long horizon. However, drastic changes in portfolio are typically associated with a change in the bank's "business model." Within a given business model, the assumed portfolio composition rule seems reasonable, especially over the three-year horizon considered in this paper.

2.5 Default Thresholds and Bankruptcy

2.5.1 Default Thresholds

Banks default if the ratio of shareholder funds to risk-weighted assets falls below 4 percent—the Basel regulatory minimum for tier 1 capital. Risk-weighted assets are computed by applying the risk weights listed in table 1. These are calibrated on the basis of the Basel II standardized approach.[13]

The Basel threshold ratio is an extreme (solvency-based) definition of the failure of a financial institution. In practice, a funding liquidity crisis is likely to result before such a ratio is breached. In future work, we intend to develop a broader set of indicators and ratios that can be used to refine the point at which crises are precipitated.

2.5.2 Bankruptcy Costs

When a bank defaults, we follow James (1991) and suppose that it incurs costs equivalent to 10 percent of its remaining assets. This is also in line with the mean figure reported in Bris, Welch, and Zhu (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

[12]Specifically, the average standard deviation is under one-tenth of the average capital ratio. Note also that the existence of fixed trigger ratios for capital below which regulators might take disciplinary action also points toward a desire amongst banks to maintain capital at a relatively constant buffer above the minimum requirement.

[13]In future work, we intend to compute endogenous risk weights on the basis of the Basel II internal ratings-based approach.

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 fulfill all of their obligations upon default.

2.6 Second-Round Impact on Banks—Feedback Effects

2.6.1 Price Effects of Asset Sales

When a bank fails, financial markets may have a limited capacity to absorb assets sold onto the market and, as a result, asset prices may be depressed. Following Schnabel and Shin (2004) and Cifuentes, Ferrucci, and Shin (2005), we suppose the following relation between forced sales and the asset price, q:

$$q = e^{-\theta x}, \tag{9}$$

where $x > 0$ is the fraction of system assets sold onto the market and the fundamental price of the asset is set at $q = 1$. The value of θ is based on calibrations of a search-based model of asset prices developed by Duffie, Gârleanu, and Pedersen (2007). In the baseline calibration, we assume that UK banks hold 10 percent of system trading assets and set $\theta = 0.81$. Our choice implies that the asset price falls by 8 percent when one-tenth of system assets have been sold in a fire sale.

We integrate equation (9) into RAMSI by assuming that trading assets can be treated as a single generic asset class on banks' balance sheets, whose price depends on the volume of assets being sold onto the market. Specifically, when a bank defaults, all of its net trading assets are sold onto the market in the same quarter.[14] This reduces the generic asset price, and other banks suffer mark-to-market losses as a result. Subsequent problems in other banks could depress the price still further, setting off the feedback loop described below.

2.6.2 Network Model

When a bank defaults, counterparty credit losses incurred by other banks are determined using a network model. A matrix of interbank

[14]This could be interpreted as deriving from attempts by the bank to save itself before formally defaulting.

exposures for the ten major banks in our model, along with some smaller UK institutions and a selection of large, complex financial institutions (LCFIs), is built using reported large exposure data, where available. Though it is only the major UK banks that can default for fundamental reasons, the additional banks in the network may transmit contagion. Furthermore, since we can force the idiosyncratic default of any institution, their inclusion allows us to obtain a partial assessment of the likely implications of the failure of a given institution on the rest of the system—something which has become increasingly important as the current crisis has progressed.

Since we have information on total interbank asset and liability positions, we use maximum entropy techniques to fill in any missing gaps in the network, ensuring that none of the estimated entries exceed the reporting threshold for large exposures.[15] If any interbank assets or liabilities are unallocated following this procedure, we assume that they are associated with interbank business with a residual sector. 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. The approach assumes that interbank claims are junior to nonbank claims. The LGD incurred by interbank creditors on their exposures is determined endogenously based on the shortfall in assets relative to liabilities of the defaulting bank (recall that bankruptcy costs imply that a bank's assets will generally be insufficient to fulfill all of its obligations upon default). Counterparty credit losses can lead to the failure of another bank, in which case it too incurs bankruptcy costs and defaults on part of its interbank obligations. The clearing algorithm solves for the unique outcome of this iterative process, determining all contagious defaults and returning final, total counterparty credit losses for each institution.

2.6.3 Feedback Loop

After accounting for counterparty credit losses and mark-to-market losses on net trading and other financial assets, we check for further

[15]The techniques adopted are similar to those discussed by Wells (2004), Elsinger, Lehar, and Summer (2006b), and Oesterreichische Nationalbank (2006). See Upper (2007) for an overview of this literature.

defaults by reapplying the default rule to banks which initially survived. In the event of a further default, we iterate around the network and asset-side feedback mechanism again. If not, we proceed to the next quarter after rebalancing all balance sheets to account for counterparty credit losses. As noted earlier, we assume that asset prices recover to pre-feedback levels, so mark-to-market losses are not carried forward. Clearly, recent events suggest that it might be more appropriate to assume a gradual adjustment process. This would impose higher systemic costs on the banking system and is something we intend to explore in future work.

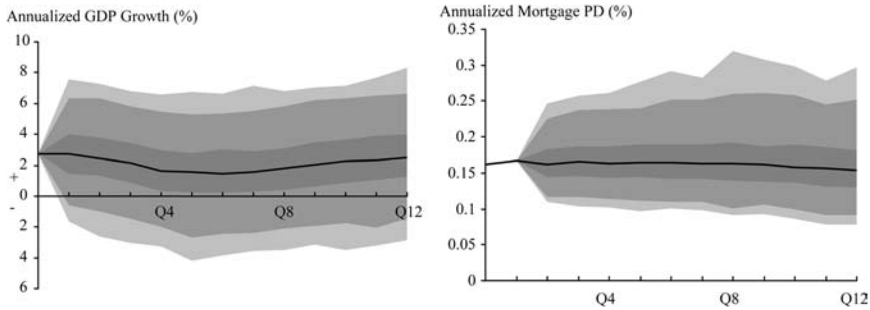
3. Simulations

We now consider the output of two sets of stochastic simulations based on alternative parameterizations of the trading book. In both cases, we use data up to 2005:Q4 (so that all balance-sheet information is on the basis of end-2005 data) and run 1,000 simulations on a three-year forecast horizon stretching to the end of 2008. Both configurations use the same seed for the random-number generator—this implies that the underlying risk factors in each case are identical. The GVAR is currently the only source of exogenous randomness in the stochastic simulations; each simulation is thus driven by a sequence of macroeconomic shocks $[(\varepsilon_t^{uk})' \ (\varepsilon_t^{us})']'$ drawn from a multivariate normal distribution.[16]

Throughout this section, we discuss results for the UK banking system in aggregate. But, since individual banks' balance sheets are at the core of RAMSI, the model produces a rich set of information and may be used both to obtain baseline projections for specific institutions and to analyze their performance under stress.

[16]In other words, we draw 1,000 realizations 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 1,000 draws. The number of simulations is admittedly rather small; furthermore, by simulating a single (multivariate) innovation in each quarter and scenario, we are effectively sampling from the underlying random tree of the model. Both limitations can be bypassed at the cost of higher computational complexity. We believe, however, that the current setup provides a good description of the properties of the model and yields several interesting qualitative results.

Figure 3. UK Risk Factors (Median, 50%, 95%, and 99% Confidence Bands)



Such information can be used to assess the vulnerability of particular institutions to different risks and may thus, in time, feed into the internal institution-specific risk-assessment work undertaken by regulators and central banks.

3.1 Risk Factors

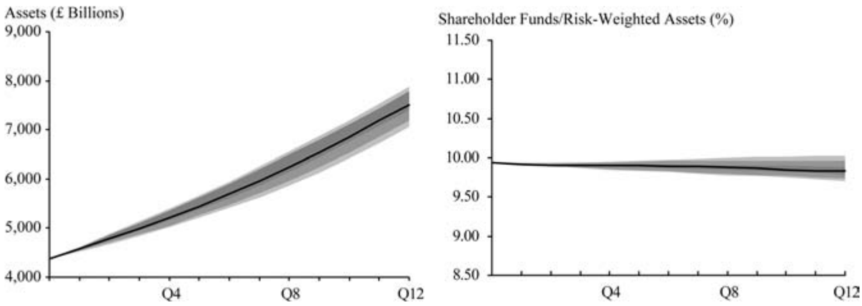
Figure 3 presents fan charts for UK GDP growth and mortgage PDs over the forecasting horizon. These are representative of the paths of macroeconomic risk factors and PDs generated by the model based on end-2005 data.[17] It is evident that there are several recessionary scenarios in the simulations. Though not shown, equity prices are highly volatile, as might be expected, and the slope of the yield curve varies considerably. Meanwhile, the variability of PDs reflects macroeconomic outcomes as implied by equation (4).

3.2 The Baseline Asset Distribution

In the first simulation exercise, we assume that no gains or losses are made on net trading assets (i.e., we set $\gamma_1 = \gamma_2 = \gamma_3 = 0$ in equation (3)). Given our somewhat arbitrary modeling of the trading book, this parameterization represents a natural benchmark. Figure 4 shows how the systemwide distributions of some of the key banking sector variables evolve over the forecasting horizon in this case.

[17]These distributions are intended to be illustrative and do not represent the views of Monetary Policy Committee members as reported in the Bank of England's *Inflation Report*.

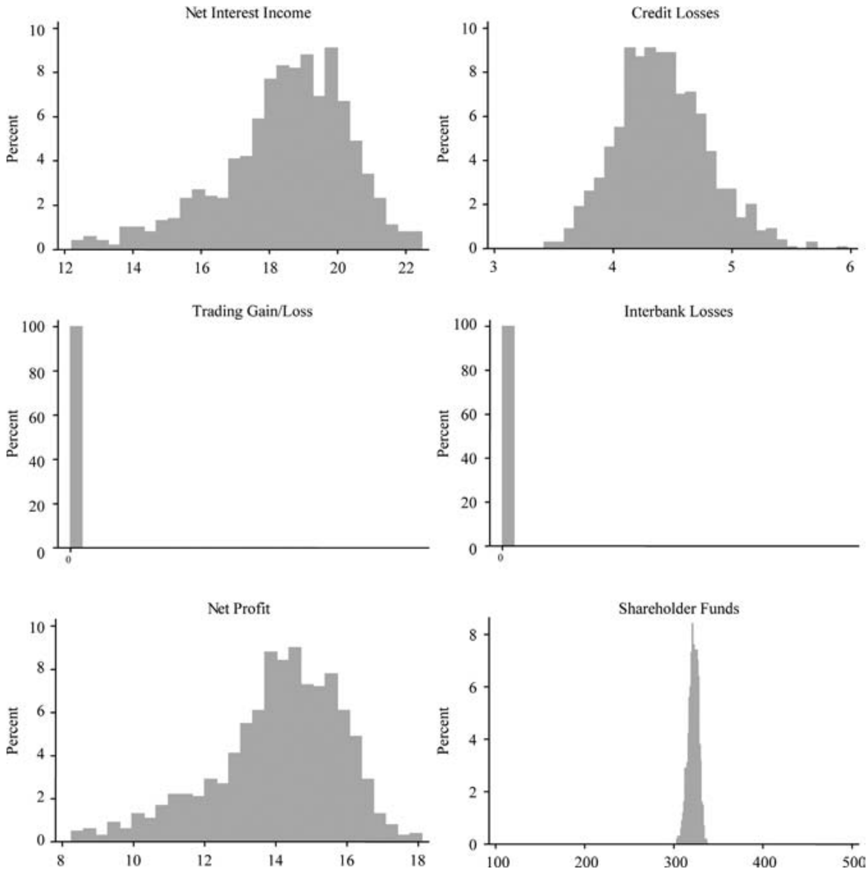
Figure 4. Banking Sector Dynamics, No Trading Book (Median, 50%, 95%, and 99% Confidence Bands)



As is clear, total banking system assets rise consistently over time. This reflects our pricing assumptions and the supplementary spreads added onto certain asset classes which imply that net interest income exceeds credit losses in expected (mean) terms by construction. Moreover, even in the worst-case outcomes in this calibration, net interest income still exceeds credit losses (see figure 5, discussed below). Partly because banks cannot make the types of trading loss experienced over the past couple of years in this simulation exercise, they are always profitable and balance sheets always expand. But, consistent with the reinvestment-rule targeting, the ratio of shareholder funds to risk-weighted assets barely changes, as seen in the right-hand panel of figure 4.

Figure 5 illustrates some of the output in a slightly different way, using the distribution of a few key variables in the final quarter (in principle, these distributions can be generated for any quarter). As can be seen, there is variation in both credit losses and net interest income, but the variance of both these distributions is relatively low in the current calibration. Interestingly, however, the net interest income distribution has a fat negative tail and hence so does the profit distribution. This reflects the zero lower bound on nominal interest rates. In scenarios for which the risk-free rate falls close to zero, banks are constrained in their ability to pay negative spreads on household and corporate deposits. As a result, their net interest income margins are squeezed. Since there is no corresponding upside effect, the net interest income distribution exhibits negative skew. By contrast, credit losses are normally distributed. A skewed, fat-tailed

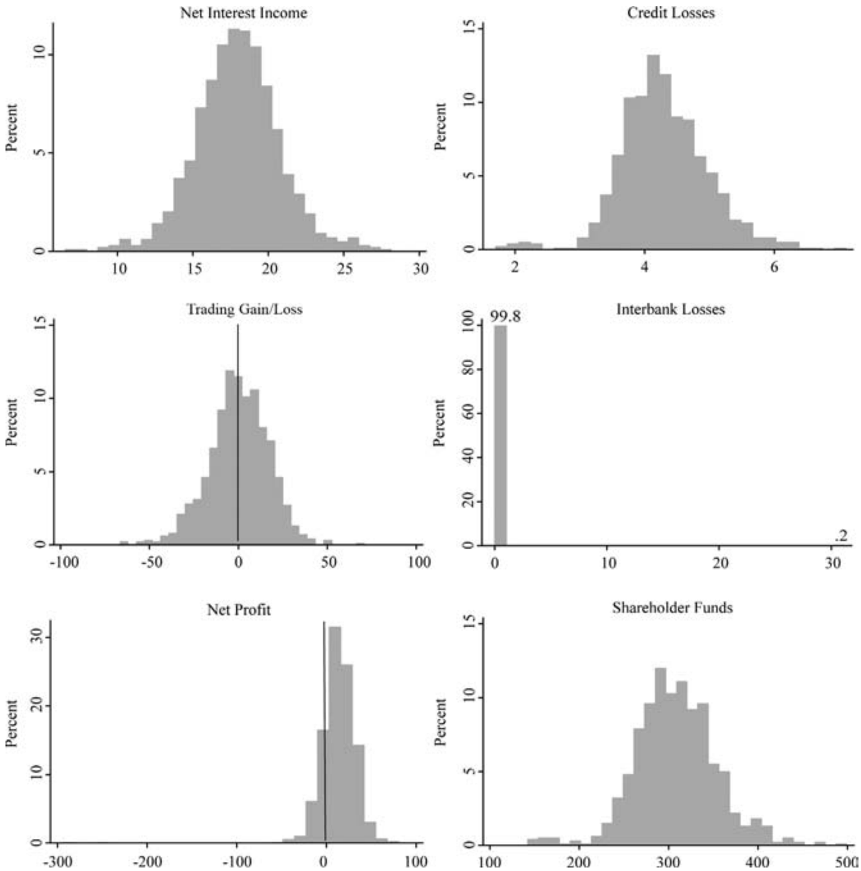
Figure 5. Final-Quarter Banking Sector Distributions (No Trading Book)—Unit: £ Billions



Note: Net profit is defined as net interest income − credit losses + trading gain/loss − bankruptcy costs.

credit loss distribution could be generated by modeling lumpy rather than granular exposures, introducing nonlinearities and correlated defaults in the PD equations, or modeling dependencies between PDs and LGDs (see, e.g., Chava, Stefanescu, and Turnbull 2006, and Das et al. 2007). Moreover, incorporating a richer set of macroeconomic risk factors, including house prices, can generate greater variation in the distribution of credit losses.

Figure 6. Final-Quarter Banking Sector Distributions (With Trading Book)—Unit: £ Billions

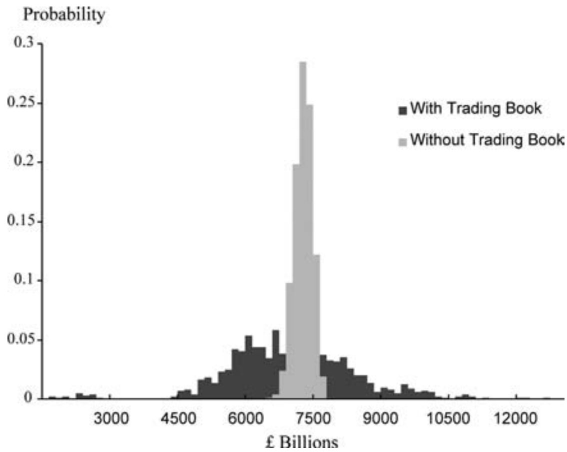


Note: Net profit is defined as net interest income − credit losses + trading gain/loss − bankruptcy costs.

3.3 Introducing Trading-Book Volatility

The second simulation exercise uses the trading-book calibration specified in section 2.3.2. As discussed, this calibration was partly chosen to ensure that fundamental defaults occur in some scenarios. Unsurprisingly, it leads to large gains and losses on net trading assets. Consequently, as is made clear by the bottom left-hand panel of figure 6, the system is no longer profitable in all scenarios. And,

Figure 7. Final System Assets Distributions (With and Without Trading Book)

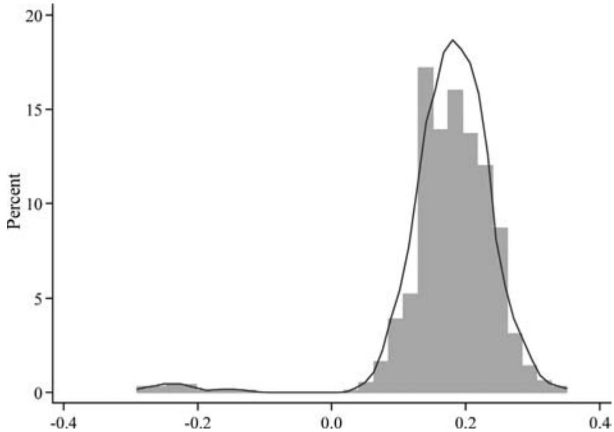


as shown in figure 7, the distribution for final banking system assets is much more volatile. Further, in some of the scenarios, the trading losses are large enough to generate defaults; there are two cases of this in the last quarter of the simulation, giving rise to the nonzero interbank losses displayed in the middle right-hand panel of figure 6.

3.4 Fundamental and Contagious Default

From figure 7, it is also clear that the final asset distribution is bimodal, with a main peak associated with a healthy banking sector and a considerably smaller second peak in the left-hand tail. This is despite the Gaussian nature of the underlying shocks. At root, bankruptcy costs are the key source of this bimodality because they create a large, discrete loss at the point of default. But network effects and adverse asset-price feedbacks have a critical role: following the default of one bank, other banks may be tipped into default due to counterparty credit losses and mark-to-market write-downs on some of their assets. If default occurs, and especially if contagion breaks out, the cumulative bankruptcy costs thus yield a systemwide outcome that is discretely and considerably worse than if the initial default is just avoided. Therefore, beyond a certain threshold, "extreme" negative outcomes become relatively more likely than "moderate" negative outcomes. This result captures a

Figure 8. Aggregate Return on Assets (%) (Quarterly Average)



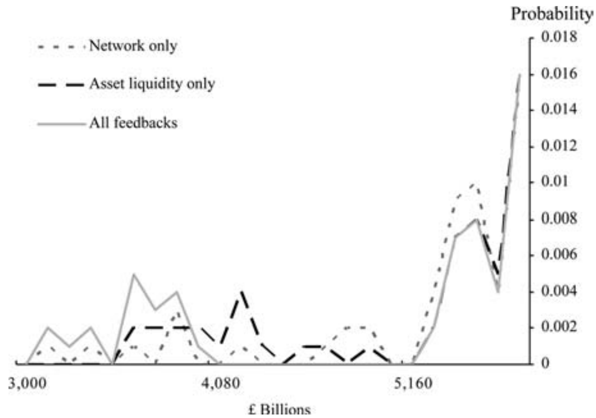
Notes: Return on assets is defined as system net profits relative to beginning-of-period assets. The line shows an estimate of the density based on normal kernels and an optimal (i.e., mean square error-minimizing) bandwidth.

phenomenon that is commonly perceived as a key feature of financial risk.

As a stock variable, total assets also reflect the step-wise nature of the default process (a bank's assets adjust smoothly in normal times, but they are no longer counted as part of the system once they have defaulted). To better illustrate that bankruptcy costs and feedbacks are material to the bimodality, their effect can be isolated by examining aggregate profits. In particular, the bimodality is clearly evident in figure 8, which shows the distribution of the aggregate return on assets averaged over the twelve quarters.

Figure 9 analyzes the bimodality in more detail by considering how our results differ if either network effects or asset-side feedbacks are excluded. The figure illustrates how these changes affect the tail of the total asset distribution. It is clear that network and asset-price feedbacks independently contribute to shaping the tail of the distribution and that, when combined, they generate a significant amplification effect. There are eighteen scenarios in which at least one fundamental default is observed. Independently of whether one or two fundamental defaults occur, a total of at least three banks

Figure 9. Tail of the Final System Assets Distribution (Various Feedback Specifications)



end up defaulting if both feedback effects are taken into account. But, even in isolation, both the network and the asset-side feedback mechanism can generate contagion. However, two contagious defaults are observed less than half the time when only one of the feedback mechanisms is active. This makes clear that the interaction of network effects and asset-side feedbacks is of prime importance when modeling contagion (see also Cifuentes, Ferrucci, and Shin 2005).

4. A Stress Scenario

To highlight the flexibility of our framework and to illustrate some of the channels captured in more detail, we now consider a specific application of the model. This takes the form of a stress test based on an illustrative scenario which combines adverse market sentiment with distress in the U.S. household and global corporate sectors. Whilst we could specify the path of all macroeconomic variables associated with this stress scenario to obtain a point estimate of its impact, we instead implement it by only imposing our priors on a subset of risk factors and parameters. This allows us to retain some of the randomness in the macroeconomic model and generate distributions conditional on the set of adverse events associated with the stress scenario.

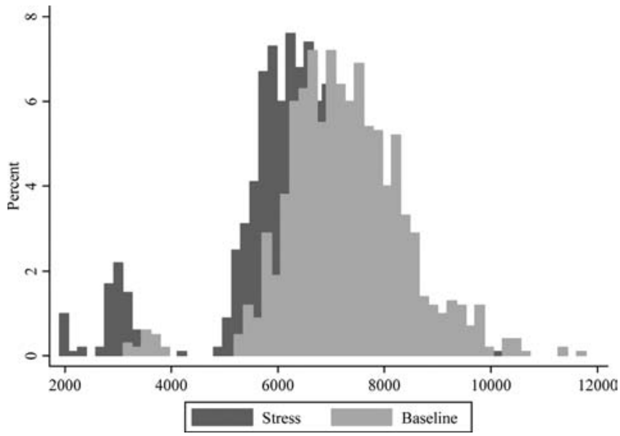
Our stress-test has four elements: real equity prices fall for one quarter; the market interbank spread goes up; PDs rise unexpectedly; and finally, markets become less liquid (i.e., asset prices become more sensitive to fire sales than in the baseline calibration). Specifically, we assume that real equity prices in both the United Kingdom and United States fall by an average of 10 percent in the first quarter, which we apply by shifting the mean of the distribution of errors of the equity equations in the GVAR. The spread of the interbank borrowing rate over the risk-free rate permanently increases from 15 basis points to 100 basis points, a level which has been reached or exceeded for much of the ongoing crisis. We also impose permanent increases in the U.S. secured (mortgage) default rate, and both the UK and U.S. corporate default rates, with the household default rate assumed to pick up from the first quarter of the simulation but the corporate default rates only increasing in the fourth quarter. These shifts represent a large but plausible shock, roughly matching the unexplained increases in PDs during the early 1990s recession in the United Kingdom.[18] Finally, we change θ in equation (9) so that fire sales cause the trading asset price to fall by 12 percent when 10 percent of system assets are sold, instead of 8 percent as in the baseline case. It is important to emphasize that this stress test is entirely meant to be illustrative and its calibration is somewhat arbitrary.

Figure 10 depicts the final asset distribution of the UK banking sector under stress. Relative to the baseline, it is clear that banks are adversely affected—the entire distribution shifts left. The greater mass in the tail in the stress scenario reflects a higher incidence of default. We also observe that the stronger liquidity feedback effect can amplify default contagion further than in the baseline; indeed, there are scenarios in which six defaults are generated.

However, there are several factors which mitigate the overall impact of the stress test. First, the fall in equity returns is not very persistent—the shock is imposed for one quarter only, so the impact

[18]Specifically, equation (4) is reestimated from 1980 to 2006 in five-year rolling regressions, holding β_1, β_2, and β_3 equal to their estimated values over the baseline sample period. The maximum intercept corresponds to the period from about 1991 through 1996. This translates to, for example, a shock of approximately 50 percent to the UK corporate PD.

Figure 10. Final System Assets under Stress-Test Scenario—Three-Year Horizon (Unit: £ Billions)



on trading assets is relatively short lived. The equity market fall causes significant losses to materialize early on before equity prices recover. Second, the higher PDs in the corporate and household sectors are gradually priced in as coupons on longer-maturity assets are repriced. Credit risk is initially underpriced, but the rise in net interest income eventually offsets higher credit losses. Finally, the rise in interbank spreads washes out to a certain extent—net borrowers in the interbank market are worse off, but lenders profit. There can, therefore, be important distributional effects within the major UK banks which are not apparent in a distribution of total system assets.

5. Conclusion

This paper developed a quantitative framework in which to gauge financial stability and assess risks to the UK banking system. The unified modeling approach sheds light on risks over and above those priced and managed by financial institutions themselves. In particular, absent intervention by the authorities, defaulting financial institutions may directly trigger default cascades as exposed counterparties take a hit to their capital and these losses are amplified by mark-to-market losses on assets due to fire sales by failed banks. Nonlinearities arising from the combination of bankruptcy costs and network and asset-price feedback effects yield bimodal simulated asset and profit distributions. This bimodality arises despite the joint normality of all risk factors and the linear modeling of credit risk and trading-book gains and losses.

Since this paper was designed to present a broad, illustrative *framework* for modeling systemic risk, there are clearly a number of areas in which the model could be developed. For example, a more sophisticated macroeconomic model including a wider range of risk factors, such as unemployment and house prices, may help to improve the fit of the probability of default equations. Additional variables would also assist with endogenizing LGDs in a meaningful way. Both of these extensions would probably increase the variation in credit losses. There is also clear scope for improving the modeling of the trading book. And the changing nature of financial intermediation highlights the importance of modeling non-interest income and attempting to capture the effects of securitization, credit-risk transfer, and off-balance-sheet items.

A more substantial area for further work is to develop our models of feedback effects on both the asset and liability sides of banks' balance sheets. RAMSI currently captures one such feedback: the impact of post-default fire sales of assets on asset prices. But the ongoing crisis has highlighted the importance of modeling the causes and implications of funding liquidity stress. Therefore, we are currently developing a set of indicators of funding stress which may be used as a guide to suggest when different funding markets may close to particular institutions. Further, by analyzing the cash-flow constraints of banks experiencing funding stress, we intend to model how banks' defensive actions, including liquidity hoarding and pre-default fire sales, may affect the rest of the financial system.

A longer-term challenge is to incorporate feedbacks from the banking sector to the real economy. In principle, this could be done by adding a reduced-form equation to the model linking realized banking sector profits and losses to the future path of the macro economy. Such an equation, though, would inevitably be difficult to formulate and estimate. Furthermore, the underlying mechanism may be partially captured by the estimated macroeconomic model, making it hard to identify the precise feedback from the banking sector. Despite these complications, the issue is highly relevant from a policy perspective and merits further investigation.

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