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# Systemic illiquidity in the interbank network

Gerardo Ferrara,<sup>(1)</sup> Sam Langfield,<sup>(2)</sup> Zijun Liu<sup>(3)</sup> and Tomohiro Ota<sup>(4)</sup>

### Abstract

We study systemic illiquidity using a unique data set on UK banks' daily cash flows, short-term interbank funding and liquid asset buffers. Failure to roll-over short-term funding or repay obligations when they fall due generates an externality in the form of systemic illiquidity. We simulate a model in which systemic illiquidity propagates in the interbank funding network over multiple days. In this setting, we show that systemic illiquidity is minimised by a macroprudential policy that skews the distribution of liquid assets towards banks that are important in the network.

**Key words:** Systemic risk, liquidity regulation, macroprudential policy.

**JEL classification:** D85, E44, E58, G28.

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# 1 Introduction

Banks lend to each other at short maturities. In this interbank network, distress can spread via insolvency or illiquidity. In terms of insolvency, one bank's liability is another's asset. Default reduces the value of the lending bank's asset, moving it closer to insolvency, and potentially generating a cascade of counterparty defaults. In terms of illiquidity, one bank's outflow of cash is another's inflow. Failure to roll-over short-term funding or repay obligations when they fall due reduces counterparties' cash inflows, potentially generating a cascade of funding shortfalls, even if banks remain solvent. This paper focuses on the latter phenomenon, which we refer to as "systemic illiquidity".

Theoretical research suggests that the probability of default cascades is increasing in the size of interbank exposures ([Nier, Yang, Yorulmazer & Alentorn, 2007](#)). Empirically, however, interbank exposures tend to be small relative to bank equity. Defaults generate counterparty losses, but these losses are typically insufficient relative to equity to trigger further insolvencies, although they might generate depositor runs ([Iyer & Peydro, 2011](#)).<sup>1</sup> By contrast, banks are vulnerable to funding shortfalls owing to their inherent liquidity mismatch ([Gorton & Pennacchi, 1990](#)). Interbank funding markets allow banks to share idiosyncratic liquidity risks ([Allen & Gale, 2000](#); [Freixas, Parigi & Rochet, 2000](#)), but also provide a channel by which funding shortfalls can propagate through the network ([Acemoglu, Ozdaglar & Tahbaz-Salehi, 2015](#)).

[Gai, Haldane & Kapadia \(2011\)](#) model liquidity contagion in a single-period setting using simulated interbank funding networks. Although useful, single-period models are liable to underestimate systemic illiquidity as they do not capture cash flow dynamics. Illiquidity becomes more likely as stress persists: even if banks survive one day, they might become illiquid after multiple days of net outflows. This is pertinent given that outflows tend to be serially correlated during banking crises: [Acharya & Merrouche \(2012\)](#) document that banks hoard liquidity as a precautionary response to scarce external funding. Such hoarding behaviour exacerbates the cost and availability of liquidity for other

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<sup>1</sup> Representative papers in the empirical literature studying solvency contagion in interbank markets are [Degryse & Nguyen \(2007\)](#) for Belgium; [Upper & Worms \(2004\)](#) and [Mimmel, Sachs & Stein \(2012\)](#) for Germany; [Mistrulli \(2011\)](#) for Italy; and [van Lelyveld & Liedorp \(2006\)](#) for the Netherlands. [Alves, Ferrari, Franchini, Heam, Jurca, Langfield, Laviola, Liedorp, Sanchez, Tavoraro & Vuillemeys \(2013\)](#) provide a cross-country analysis of contagion in a network of 53 large EU banks.

banks.<sup>2</sup> In an effort to reduce banks' liquidity mismatches, the Basel Committee devised a Liquidity Coverage Ratio (LCR) requirement, which stipulates that banks must have an adequate stock of unencumbered high-quality liquid assets to meet their liquidity needs for a 30-day liquidity stress scenario ([Basel Committee on Banking Supervision, 2013a](#)).

Our contribution is to extend the dynamic programming algorithm of [Eisenberg & Noe \(2001\)](#) to multiple time periods. This multi-period setting allows us to evaluate the effect of the LCR in reducing systemic illiquidity, and to compare this effect to other macroprudential policy designs. Moreover, we bring our model to unique regulatory data. From Bank of England returns at the end of 2013, we obtain information on 182 banks' expected future cash inflows and outflows at daily frequency. Banks receive repayments from counterparties to unsecured lending and reverse repo transactions, and provide repayments to counterparties to unsecured debts, repos, wholesale deposits, bonds and notes. Crucially, we observe cash inflows and outflows bilaterally between two given banks in the funding network. These bank-to-bank cash flow data are combined with bank-level information on liquid asset holdings.

These granular data elicit novel insights when viewed through the lens of our multi-period model. Our results indicate that the potential for systemic illiquidity in the UK interbank network was low at the end of 2013: in simulations, no bank falls short of funding because counterparties fail to repay obligations. At £70bn, the UK interbank funding network at the end of 2013 was much smaller than banks' holdings of liquid assets, which amounted to £724bn.<sup>3</sup> In our model, systemic illiquidity only emerges when liquid assets are envisaged to be 50% or less of their end-2013 levels—which broadly corresponds to pre-crisis liquid asset holdings. This finding underscores the importance of post-crisis microprudential liquidity requirements, notably the LCR and its forerunners in the UK, in improving systemic stability.<sup>4</sup>

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<sup>2</sup> [Shin \(2009\)](#) describes how endogenous hoarding behaviour was at work in summer 2007, when the day-by-day deterioration of interbank funding markets eventually led to the UK government's nationalisation of Northern Rock. Similar dynamics led to the bankruptcy of Lehman Brothers ([Duffie, 2010](#)).

<sup>3</sup> We define the interbank funding network as the network of unsecured lending and repos backed by low-quality assets (i.e. assets not eligible for inclusion in the liquid asset buffer under the LCR) between banks, with maturity less than a month. The data are discussed in more detail in [Section 3](#).

<sup>4</sup> Although the phase-in of LCR requirements only began in 2015 in the EU, following the entry into force of the Capital Requirements Regulation, the UK was an early adopter of similar requirements beginning in 2009.

Furthermore, our model allows us to differentiate between “individually illiquid” banks (whose liquid asset buffers are insufficient to meet net cash outflows even in the absence of defaults by other banks) and “systemically illiquid” banks (which become illiquid owing to the failure of other banks to honour their obligations). Banks whose individual illiquidity generates systemic illiquidity can therefore be said to be systemically important in the interbank funding network. We find that banks’ degree of systemic importance is not correlated with banks’ total lending or borrowing within the interbank funding network. Instead, network structure—that is, the cross-sectional distribution of banks’ lending and borrowing—determines banks’ systemicity. Thus, it is not *how much* a bank borrows and lends, but *to whom* it borrows and lends, that determines systemic importance in the interbank funding network.

Our model sheds light on the design of liquidity regulation. Current liquidity requirements, including the LCR and the forthcoming Net Stable Funding Ratio (NSFR), are microprudential in the sense that they apply uniformly to all banks, regardless of the degree of systemic importance. Under the LCR requirement, for example, *all* banks must hold enough liquid assets, such as cash or Treasury bonds, to cover net outflows of liquidity over one month of stressed conditions. We compare this microprudential benchmark to macroprudential liquidity requirements which vary in the cross-section of banks.<sup>5</sup> We calculate the optimal cross-sectional distribution of liquid assets that minimises systemic illiquidity for a given aggregate volume of liquid asset holdings. This constrained optimisation problem is solved by requiring systemically important banks to hold more liquid assets than other, less important, banks. Given that it is privately costly for banks to hold liquid assets, our findings reveal that macroprudential liquidity requirements would improve the efficiency of purely microprudential requirements in mitigating systemic illiquidity.

To model systemic illiquidity in the interbank funding network, we take the configuration of the UK interbank funding network at the end of 2013 as given. Our approach is therefore distinct from theoretical work that seeks to explain the existence of the interbank funding network as an equilibrium phenomenon that allows banks to minimise their holdings of low-return liquid assets by sharing idiosyncratic liquidity risks ([Allen & Gale](#),

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<sup>5</sup> These macroprudential liquidity requirements can be interpreted as the quantity-based analogue to a price-based Pigovian tax on systemic importance ([Perotti & Suarez, 2011](#))

2000; Freixas et al., 2000). Instead, our paper is more closely related to the numerical literature on systemic liquidity risk. Lee (2013) simulates a simple model of hypothetical banking systems to study the effects of different network structures on systemic liquidity risk. Gai et al. (2011) develop a rich model of the interbank funding market that encapsulates unsecured loans, secured loans and haircuts on collateral. Numerical simulations of their model show that shocks to haircuts could trigger widespread funding contagion, especially when the interbank network is concentrated. Similarly, Iori, Jafarey & Padilla (2006) find that bank heterogeneity can lead to systemic illiquidity.

Owing to lack of data availability, these models of systemic illiquidity are not calibrated to real-world interbank funding networks. In earlier work, payments systems have proven a fruitful source of such data. Furfine (2003), for example, finds that the US federal funds market is robust to solvency contagion but vulnerable to liquidity contagion. Such analyses provide useful insights regarding vulnerabilities in payments systems, but suffer from the obvious drawback of focusing only on a subset of the interbank funding market. By contrast, our analysis draws on data from all relevant sources of interbank funding, including repurchase agreements.

The rest of the paper is organized as follows. In Section 2, we introduce the methodology, before describing the dataset in Section 3. Section 4 evaluates systemic illiquidity under different network configurations. To infer policy implications, we calculate the socially optimal distribution of liquid assets in Section 5. Finally, Section 6 concludes.

## 2 Model

We build a multi-period model of the interbank funding network comprised of heterogeneous banks. Banks lend to and borrow from other banks in the network via unsecured lending and repo contracts. Banks also obtain wholesale funding from other financial institutions outside the interbank network. In the spirit of the LCR requirement, we model a stress scenario in which all banks lose access to wholesale funding, and may only use their unencumbered high-quality liquid asset buffers (LAB) to meet obligations. A bank is illiquid (and defaults on its short-run liabilities) when its unencumbered liquid assets are insufficient to meet contractual obligations on any given day. This framework, and the interbank payments model that it encompasses, is described below.

## 2.1 Framework

A common metric for liquidity risk used by microprudential bank regulators is the time period that banks would survive a wholesale funding market freeze by converting their liquid asset buffers into cash (Basel Committee on Banking Supervision, 2013b). In the hypothetical scenario of a market freeze, banks are deemed unable to obtain any new loans or roll-over existing debts. Individual banks' liquidity adequacy is determined by assuming that all other banks are fully liquid, and therefore able to repay maturing debts. This microprudential assumption overlooks a negative externality, which arises when a bank fails to repay obligations when they fall due, reducing counterparties' cash inflows. To account for this externality, we allow for the fact that a defaulting bank will not repay its interbank obligations. If the externality is sufficiently strong, these creditor banks will also become illiquid—even if they were deemed to have adequate liquid asset buffers in microprudential terms when negative externalities were not considered. We call such banks “individually liquid but systemically illiquid”.

The negative externality could propagate further. Systemically illiquid banks will also stop repaying their interbank obligations, imposing a negative externality on other banks' liquid asset buffers, and generating further systemic illiquidity. Our model captures this propagation process within the interbank funding network in the following sequence.

1. On day 0, each bank holds a given quantity of liquid assets.
2. The stress scenario starts in day 1. Banks are (by assumption) unable to roll-over any existing debt or obtain new loans. All loans with an open maturity are terminated on day 1.
3. Loans with a two-day maturity are terminated on day 2, three-day loans on day 3, and so on for the subsequent 22 business days. Banks' liquid asset holdings evolve in accordance with their cash outflows over those 22 days.<sup>6</sup>
4. A bank defaults if it does not have enough liquid assets to meet its obligations.

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<sup>6</sup> For consistency with UK regulation and international standards (i.e. the LCR requirement defined by the Basel Committee), we focus on banks' liquidity positions over one month, i.e. 22 business days.

5. If a bank defaults, its counterparties will not receive any future scheduled payments from that bank, but still need to repay any debt due to that bank.<sup>7</sup> This in turn affects other banks' liquid asset holdings.
6. If other banks default, repeat step 5.

Systemic illiquidity is measured in two ways. First, we count the number of banks that default, or default earlier than otherwise, due to systemic illiquidity. If a bank remains liquid throughout the 22-day stress period up to step 4 above, but defaults when we take systemic illiquidity into account (in steps 5 and 6), we say that the bank defaults due to systemic illiquidity; it is “individually liquid but systemically illiquid”. If a bank defaults due to individual liquidity mismatches (in step 2 or 3), but defaults earlier when we take systemic illiquidity into account, we say that the bank defaults earlier due to systemic illiquidity.

Second, we calculate the proportion of the banking system that would default, or default earlier, due to systemic illiquidity. To do this, we infer banks' relative importance from their “impact score”, which is a regulatory measure of the potential impact of firms' failure on the stability of the system as whole, taking into account balance sheet variables, such as total assets, as well as the critical financial services provided by firms.<sup>8</sup> To put this impact score into context, the bank with the highest impact score accounts for 12% of the UK banking system's aggregate impact score. If this bank were to default in our simulations, we would say that 12% of the UK banking system is in default.

## 2.2 Interbank payments model

The network is populated by  $N$  institutions, each of which is identified by  $i, j \in [1, N]$ . There are two types of liabilities: unsecured lending and repo contracts. In the one-period Eisenberg-Noe model, there are  $N$  nodes that have certain contractual obligations

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<sup>7</sup> For repos, we assume that all future payments are netted and settled immediately upon the default of the counterparty. Our results remain qualitatively similar if we assume that settlement takes place outside the 22-day period.

<sup>8</sup> The potential impact score is used by the Bank of England's Prudential Regulation Authority (PRA) to quantify the potential impact that a firm could have on financial stability. As such, it is a key component of the PRA's risk framework (see <http://www.bankofengland.co.uk/publications/Documents/other/pr/bankingappr1210.pdf>). We use the PRA's impact score—instead of a simpler measure such as total assets—because some firms, e.g. custodian banks, have small balance sheets but large potential impact.



to each other. Node  $i$  has an initial LAB of  $e_i$  and has total nominal liabilities  $p_i$ . The fraction of its total liabilities owed to node  $j$  is denoted by  $\Pi_{ij}$ . The terminal LAB  $w_j$  of node  $j$  can be calculated by

$$w_j = e_j + \sum_{i \neq j} p_i \Pi_{ij} - p_j \quad (2.1)$$

where  $\sum_{i \neq j} p_i \Pi_{ij}$  represents the total payments received by  $j$  from other banks.

The algorithm finds a unique payment vector that is consistent with three regulatory requirements: (i) seniority of debt over equity, (ii) limited liability of equity, and (iii) proportional repayment. In addition, we impose three common sense rules, namely that (iv) payments are non-negative, (v) payments do not exceed liabilities, and (vi) default is to be avoided if possible.

The vectors  $\mathbf{p}^*$  can be calculated as an optimal solution of the following optimisation problem:

$$\operatorname{argmax}_{\mathbf{p}^*} \mathbf{1} * \mathbf{p}^* \quad (2.2)$$

subject to

$$p_j^* \leq e_j + \sum_{i \neq j} p_i^* \Pi_{ij} \quad \forall j$$

$$0 \leq p_j^* \leq p_j \quad \forall j.$$

That is,  $\mathbf{p}^*$  can be found by maximizing a sum of all nodes' payments, subject to the constraints that a bank's payment is non-negative, cannot exceed its promised payment, and cannot exceed what it receives from other banks by more than its initial wealth.

In a multi-period model, we introduce time, indexed by  $t$ , which is discrete (at daily frequency) and finite (with a horizon  $T$  of one calendar month, i.e. 22 business days). In this setting, we find a payment vector that is consistent with the six rules listed previously.

The optimal payment vectors  $\mathbf{p}^*$  can be calculated by optimising:

$$\begin{aligned} & \underset{\mathbf{p}^*}{\operatorname{argmax}} \sum_{t=1}^T 1 * \mathbf{p}^{*t} & (2.3) \\ & \text{subject to} \\ & p_j^{*T} \leq e_j^T + \sum_{t=1}^T \sum_{i \neq j} p_i^{*t} \Pi_{ij}^t & \forall j \forall T \\ & 0 \leq p_j^{*t} \leq p_j^t & \forall j \forall t. \end{aligned}$$

In summary, we reformulate the one-period [Eisenberg & Noe \(2001\)](#) problem by introducing a time component for each equation. This model optimises banks' payments over multiple periods, and allows us to distinguish between periods in which a bank is a going concern, in the process of defaulting, or has defaulted, either due to individual illiquidity or systemic illiquidity.

## 3 Data

To carry out the simulation exercises, we combine two regulatory datasets. First, we estimate banks' liquidity positions over one calendar month, assuming that banks cannot borrow new funds or roll-over their existing debt. Second, we build a network of banks that are connected to each other via contractual repayment obligations. For both datasets, we use the same reporting date of 31 December 2013. This section describes the construction of these two datasets.

### 3.1 Estimating banks' liquidity positions

In regulatory returns, UK banks are obliged to report their liquid asset buffer as well as their expected future cash inflows and outflows on a daily basis over a specific time horizon as part of their Recovery and Resolution Planning (RRP) and other regulatory reporting. These filings allow us to calculate banks' daily liquid asset buffers on the reporting date and during the stress scenario, under the assumption that banks cannot obtain any additional funding and can only use liquid asset buffers to meet obligations.

We focus on wholesale cash flows only; retail assets and liabilities are assumed to stay constant over the stress period.

Banks report granular wholesale cash inflows and outflows, and we take account of all flows to estimate their daily liquidity positions. On the cash inflow side, banks receive repayments from their unsecured lending and reverse repo transactions. On the cash outflow side, banks repay unsecured debts, repos, wholesale deposits, redemptions of bonds and notes they have issued, and other miscellaneous cash flows. By netting these cash inflows and outflows, we obtain banks' future liquidity positions at a daily frequency.

### 3.2 Estimating dynamic networks

We estimate the network of banks' bilateral payment obligations each day. To do this, we estimate a  $(N \times N \times T)$  matrix, where  $N$  is the number of counterparties and  $T$  is the 22-day duration of the liquidity stress scenario. No existing dataset contains banks' daily repayments to each of their counterparties; to fill this gap, we estimate daily funding networks with the following two inputs.

First, UK banks report their top 30 funding providers, including the total amount borrowed and weighted average maturity, but without a detailed maturity breakdown. This provides information on funding connections between banks. Second, UK banks report their top 20 bank counterparties to which they are exposed ([Langfield, Liu & Ota, 2014](#)). Since the reported bilateral exposures are broken down by instrument (e.g. unsecured loans, repos, and so on), we can identify bilateral repayments. Another benefit of this dataset is that bilateral exposures are broken down by maturity (overnight, within three months, and longer than three months), permitting us to define the time profile of contractual obligations. In the data, most interbank funding is provided overnight (see [Figure 1](#)).

To create the interbank funding network, we first populate a matrix with data on bilateral interbank funding links from the datasets described above. We include only unsecured lending and repos collateralised with assets that are not eligible for inclusion in the liquid asset buffer. We then use a maximum entropy algorithm to estimate the funding network for each of the 22 days.

Since the network matrices are estimated based on incomplete data, there are three potential shortcomings of our approach. First, the networks capture only large funding connections. This is because we collect counterparty-to-counterparty information from two regulatory datasets that report only the largest 20-30 counterparties. Smaller liabilities and exposures are not reported in the datasets and therefore not included in our estimated network. While the absolute size of these missing connections may be small, they may lead to underestimation of systemic illiquidity.

Second, since the regulatory datasets are collected from UK banks only, our network does not cover connections with non-UK banks or non-banks. This is potentially a significant limitation given that UK banks' unsecured borrowings from other UK banks are approximately half of their unsecured borrowings from non-UK banks, and one-tenth of their unsecured borrowings from non-bank financial institutions. Moreover, our sample covers 90.7% of UK interbank unsecured loans, but only 20.8% of interbank repos. Our low coverage of repo transactions arises from the fact that UK banks are reliant for funding on foreign repo lenders (Langfield et al., 2014). In addition to unsecured interbank lending, we focus on repos backed by low-quality assets, which tend to experience significant declines in market value during a wholesale funding stress and hence have negative implications for banks' liquidity positions.

Third, we use a maximum entropy algorithm to estimate the matrix of liabilities for each bank day-by-day (see the [Appendix](#) for technical details). The algorithm estimates all elements of a matrix from the vectors of column-sum and row-sum. As the degree of freedom when the algorithm estimates a  $N \times N$  square matrix is  $N \times N - 3N$  (since the diagonal elements of the matrix are known to be zero, the number of elements to be estimated is  $N \times N - N$ ), the algorithm spreads the elements as evenly as possible over the whole matrix as long as the elements are consistent with the column-sums and the row-sums. Since we use the algorithm to estimate a matrix of (lenders)  $\times$  (maturities up to a calendar month), the algorithm spreads the liabilities evenly throughout the maturity buckets, as long as these are consistent with the borrowing bank's cash flow schedule. We place additional constraints upon the solution based on prior expectations. These additional constraints greatly improve the quality of the estimation by using banks' average

maturity data and recovery and resolution planning data broken down by maturity.<sup>9</sup> This informative prior reduces the region of unknown activity between banks.

Table 1 summarises the volumes of interbank funding among the 182 banks in our sample and over the 22 days of our liquidity stress scenario. At the beginning of the simulation, banks on average receive funding from 3.28 other banks. There is considerable cross-sectional variation around this mean, represented by the relatively large standard deviation, driven by a long right tail of banks with funding connections with many other banks. Over the 22-day stress scenario, the mean degree decreases, as funding is concentrated at shorter maturities. The largest drop occurs between day 1 and day 2, reflecting the disproportionately large share of overnight funding contracts (see Figure 1). Likewise, the mean strength of each link in the network deteriorates from £233mn on day 1 to £12mn at the end of the liquidity stress scenario on day 22.

## 4 Results

### 4.1 Illiquidity in the observed interbank network

Let us begin by considering the case in which banks hold the liquid asset buffer that they held at the end of 2013. With these inputs, and in an adverse scenario in which banks are unable to roll-over their short-term wholesale funding, two banks would default owing to individual liquidity mismatches (as shown in Figure 2). No systemic illiquidity is present, however, as the two defaulting banks do not cause any other banks to become illiquid during the 22-day period.

This result is not surprising, since the total size of the interbank funding network—the sum of weighted links between banks—was only around £70bn at the end of 2013. This is much smaller than the £724bn of liquid asset buffers then held by banks. Under these conditions, most banks would withstand the adverse 22-day scenario envisaged by our simulations, and the only two banks that default in our first simulation do not generate

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<sup>9</sup> We estimate a  $(182 \times 22)$  matrix for each bank where, theoretically, the degree of freedom is  $(182 \times 22 - 182 - 22 = 3,800)$ . In practice, for the overnight payments, we have constrained 99.2% of the free elements—by far the largest component in the network of interbank loans. Additionally, we have fixed approximately one third of the elements of the matrices that the algorithm estimates, reducing the degrees of freedom by up to 2,538. This way, our approach identifies several important links, and loads them with the largest possible exposures consistent with the cash-inflow and cash-outflow constraints, generating more realistic network features and without overestimating contagion.

any systemic illiquidity. Therefore, according to our model, liquidity contagion would not occur in a 22-day liquidity stress scenario given the network configuration of interbank funding and the levels of liquid asset buffers that prevailed at the end of 2013.

Nonetheless, we cannot safely conclude that the UK interbank system is immune to liquidity contagion. In 2013, UK banks' liquid asset holdings were well in excess of regulatory guidance ([Bank of England, 2013](#)). Before the crisis, however, UK banks held much lower levels of liquid assets, and the volumes interbank lending were larger ([Figure 3](#)). In addition, liquid asset holdings cover not only wholesale cash outflows but also other cash outflows such as retail deposits and margin calls, which are not modelled in this paper, but which are likely to further deteriorate the liquidity position of banks during a stress period. Taken together, these insights suggest that systemic illiquidity could be present when interbank lending is large relative to banks' liquid asset holdings, as was the case before the crisis.

## 4.2 Illiquidity in an enlarged interbank network

To shed further light on the sensitivity of systemic illiquidity, we model an interbank network in which the size of interbank lending is large relative to banks' liquid asset holdings. This can be done by increasing the size of interbank lending or reducing the liquid asset buffers (or both). When doing so, we multiply the true end-2013 interbank network and banks' liquid asset buffer holdings by a constant scalar, so that the network structure and the distribution of liquid asset buffers remain unchanged.

To re-create the pre-crisis situation with respect to liquid asset holdings and interbank markets, we set banks' liquid asset holdings at 50% of their end-2013 levels, and the size of the interbank funding network, defined as the sum of weighted links between all banks, at 300% of that which prevailed at the end of 2013. The simulation results under these assumptions are shown in [Figure 4](#). Of the 182 sample banks, 9 default during the 22-day period due to individual liquidity mismatches. The default of these 9 banks generates substantial systemic illiquidity, as other banks do not receive scheduled payments from the 9 defaulting banks. Consequently, the simulation reveals that a further 16 banks would default or default earlier due to systemic illiquidity.

Figure 5 illustrates a richer set of simulation results by varying the level of banks' liquid asset buffers as a percentage of their end-2013 holdings, while keeping network size at 300% of the end-2013 level. Liquidity contagion occurs when liquid asset buffers are up to 65% of banks' end-2013 holdings. However, the number of systemically illiquid banks and the proportion of the banking system in default owing to systemic illiquidity is not necessarily monotonically decreasing in the size of banks' liquid asset buffers, because banks may become individually illiquid (and hence not systemically illiquid) when they do not hold sufficient liquid asset buffers. If a bank does not hold enough liquid assets to cover its individual liquidity mismatch, it will never default due to systemic illiquidity, because it will default due to individual liquidity mismatch in the first place in the stress scenario.

Figure 6 shows systemic illiquidity as a function of both liquid asset buffers and network size. When banks hold their end-2013 liquid asset buffers, liquidity contagion does not occur even with increased network size, because few banks default due to individual liquidity mismatches and trigger contagion. By contrast, when banks' liquid asset buffers are below 50% of their end-2013 holdings, the number of additional and early defaults, and the proportion of the banking system in default, owing to systemic illiquidity is substantial.

### 4.3 Illiquidity with exogenous default

Next, we examine the impact of the failure of a major bank in the network. For this, we assume that a major bank exogenously defaults on day 1.<sup>10</sup> This is a plausible antecedent scenario in the sense that the default of a major bank could trigger widespread stress in the wholesale funding market. Analytically, it enables us to assess the importance of each bank in terms of their contribution to systemic illiquidity. The results of these simulations, shown in Figure 7, reveal that contributions to systemic illiquidity vary greatly across banks, and remain significant for a small subset of banks even when liquid asset buffers are 100% of their end-2013 levels. Again, systemic illiquidity is not monotonically decreasing in the size of liquid asset buffers because vulnerable banks are more likely to default due to individual liquidity mismatches when liquid asset buffers are small.

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<sup>10</sup> A major bank is defined as one of the 19 banks with the highest impact scores.

## 4.4 Explaining banks' contributions to systemic illiquidity

What drives the cross-sectional variation in the impact of the exogenous failure of each of the 182 banks? To explore this question, we estimate a linear regression model in which the proportion of the banking system in default under each simulation scenario is regressed on several potential determinants, the summary statistics of which are presented in Table 2. Most obviously, this includes *Ownimpact*, which is the impact score of bank  $i$ , namely the bank assumed to default at the beginning of the stress scenario. The failure of a bank with a greater impact score is expected to generate more systemic illiquidity, and indeed we estimate positive coefficients, significant at the 1% confidence level, in all specifications reported in Table 3. The magnitude of the estimated coefficient is such that, in the specification reported in column 6, a two standard deviation increase in *Ownimpact* is associated with a 1.4 standard deviation increase in the proportion of the banking system in default. The economic magnitude is therefore very large, which is intuitive: a bank's impact score is precisely intended to capture the importance of that bank vis-à-vis the rest of the banking system.

Interestingly, however, we find that *Ownimpact* is not the only variable of significance in explaining cross-sectional variation in the dependent variable. In particular, we find that *WeightedinstrengthLAB* is statistically significant at the 1% confidence level. This variable measures the size of bank  $i$ 's borrowing from bank  $j$ , scaled by bank  $j$ 's liquid asset holdings and impact score.<sup>11</sup> In the regression reported in column 6 of Table 3, a two standard deviation increase in *WeightedinstrengthLAB* is associated with a 0.4 standard deviation increase in the proportion of the banking system in default. Intuitively, *WeightedinstrengthLAB* captures the importance of bank  $i$  in the interbank funding network: if bank  $i$  is a large borrower from other banks relative to their holdings of liquid assets, and the banks from which bank  $i$  borrows have large impact scores, then bank  $i$ 's effect on systemic illiquidity will be correspondingly greater.<sup>12</sup> When bank  $i$  defaults, it

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<sup>11</sup> Formally, *WeightedinstrengthLAB* is defined as  $\sum_j \frac{B_{ij}}{L_j} S_j$ , where  $B_{ij}$  is the borrowing of bank  $i$  from bank  $j$ ,  $L_j$  is the liquid asset holdings (after deducting net flows in the stress scenario) of bank  $j$ , and  $S_j$  is the impact score of bank  $j$ .

<sup>12</sup> Comparison of columns 5 and 6 of Table 3 reveals that it is important to scale *WeightedinstrengthLAB* by bank  $j$ 's impact score. The estimated coefficient of a similar variable which does not scale by bank  $j$ 's impact score, namely *instrengthLAB*, is statistically insignificant. Intuitively, bank  $i$ 's borrowings from other banks might be large relative to their liquid asset holdings, but if those banks have low impact scores, the effect on the dependent variable will be limited.



fails to honour its obligations to other banks, for whom the non-payment is large relative to liquid asset holdings. This intuition helps to explain why we estimate a statistically and economically strong effect of *WeightedinstrengthLAB* in explaining cross-sectional variation in the proportion of the banking system in default following bank  $i$ 's failure, in addition to the explanatory role played by *Ownimpact*.

Unweighted network measures are statistically or economically less important. The coefficient of *Betweenness*, which measures the extent to which bank  $i$  lies “between” links among other banks, is estimated to be statistically insignificant in columns 4-6 of [Table 3](#), and only mildly significant at the 5% confidence level in a univariate regression in column 2. Although betweenness captures a bank’s centrality, it does not reflect the size of its activity in the interbank funding network, unlike *Ownimpact* and *WeightedinstrengthLAB*.

Finally, we turn to *Loginstrength*, which measures the total borrowing of bank  $i$  from other banks in the interbank funding network. We estimate a statistically significant positive coefficient of *Loginstrength* in the univariate regression reported in column 3 of [Table 3](#), but negative coefficients in columns 4-6. This reflects the positive correlation of *Loginstrength* with respect to variables such as *Ownimpact* and *WeightedinstrengthLAB*. Once the latter variables are controlled for, the estimated coefficient of *Loginstrength* switches sign. Although this may appear surprising, the economic magnitude of the predicted effect is negligible. The intuition is that the default of a particular bank would only generate significant systemic illiquidity if it borrows from banks that are vulnerable. As such, the size of interbank borrowing is a poor metric for banks’ contribution to systemic illiquidity.

Wrapping up, the regression estimates reported in [Table 3](#) suggests that it is how much a bank borrows *from whom*, rather than the size of interbank borrowing per se, that determines a bank’s contribution to systemic illiquidity, in addition to its own impact score. This insight motivates the next section, in which we conduct a policy experiment based on the joint distribution of interbank borrowing and liquid asset holdings.

## 5 Policy experiment

In this section we conduct a policy experiment. We ask: how should macroprudential liquidity requirements be designed so as to minimise systemic illiquidity across simulation draws? To motivate this question, we begin by recapping the rationale for liquidity regulation. Given that stringent aggregate liquidity requirements increase the cost of liquidity transformation for banks, the *distribution* of those requirements in the cross-section of banks is a useful object of study. Through the lens of our multi-period simulation model, we evaluate whether a macroprudential distribution of liquidity requirements, in which network effects and systemic illiquidity are taken into account, can improve upon the microprudential (uniform) distribution on which current regulation is based.

### 5.1 Rationale for liquidity regulation

The business model of banks entails substantial liquidity and maturity mismatch. Banks therefore have an inherent exposure to funding liquidity risk; the results presented in [Section 4](#) confirm that the interbank market can indeed facilitate substantial systemic illiquidity under certain conditions. This externality of systemic illiquidity justifies policy intervention in banks' liquidity and maturity mismatches in general and their interbank market activities in particular.

Policymakers have a range of tools at their disposal to mitigate banks' liquidity risk. In the classical banking literature, common deposit insurance can prevent idiosyncratic bank runs ([Diamond & Dybvig, 1983](#)). However, deposit insurance reduces incentives for depositors to monitor banks' activities and for banks to self-insure against liquidity risk. In recognition of this moral hazard, most real-world deposit insurance schemes only cover retail deposits up to a certain threshold. This maintains the incentive of sophisticated wholesale depositors to exert discipline on banks' funding liquidity risk. The downside, however, is that a retail-only deposit insurance scheme cannot offer full protection against runs when banks are substantially funded by wholesale deposits.

The ultimate backstop against runs is the central bank, which has the capacity to act as lender of last resort (LOLR), for instance by providing liquidity at the discount window to illiquid-but-solvent institutions. Central banks' LOLR facilities are effective in reducing systemic illiquidity, but like fully-fledged deposit insurance they distort incentives. Ex-

ante, LOLR-eligible institutions anticipate that they will receive funding from the LOLR in the event of a liquidity shortfall, so they have a private incentive to take socially excessive funding liquidity risks (Acharya, Drechsler & Schnabl, 2014). Ex-post, LOLR-eligible institutions with low franchise value have an incentive to extract rent from the subsidy implicit in under-collateralised LOLR facilities by shifting downside credit risk onto the LOLR (Drechsler, Drechsel, Marques-Ibanez & Schnabl, 2016).

In theory, these incentive problems associated with central banks' LOLR facilities could be mitigated by carefully screening LOLR-eligible institutions—for instance by providing liquidity assistance only at a penalty rate or at a rate calibrated to banks' credit risk. But penalty and risk-adjusted rates are not time consistent: given their mandate, central banks cannot credibly commit to a policy of “benign neglect”, with a restricted provision of liquidity, in the event of a systemic crisis. Moreover, careful screening of banks' solvency positions is frustrated by the practical difficulty of distinguishing merely illiquid institutions from insolvent institutions, particularly during systemic banking crises.

## 5.2 Microprudential liquidity requirements: LCR and NSFR

To reduce moral hazard, central banks' LOLR facilities should be economised upon. Enter liquidity regulation. New liquidity requirements—the LCR and NSFR—aim to decrease banks' reliance on LOLR facilities, and the moral hazard that this entails, by decreasing banks' liquidity risks (Stein, 2013). These predominantly microprudential liquidity requirements are crucial in offsetting the moral hazard generated by backstops such as deposit insurance and central banks' LOLR facilities (Ratnovski, 2009; Cao & Illing, 2011; Farhi & Tirole, 2012).

If holding liquid assets were costless, the optimal policy solution would be to require banks to hold as many liquid assets as necessary to negate banks' liquidity risks. However, holding liquid assets is likely to increase the cost of liquidity and maturity transformation for banks. As a result, it is important to calibrate liquidity requirements efficiently, such that banks' liquidity risks are minimised without unduly increasing the cost of liquidity and maturity transformation. In its current formulation, the liquidity coverage requirement requires banks to hold enough unencumbered high-quality liquid assets (with differential weights) to meet stressed outflows over one month (Basel Committee on Banking

[Supervision, 2013a](#)).<sup>13</sup> The net stable funding requirement will require banks to hold a certain quantity of stable funding (defined as customer deposits, long-term wholesale funding and equity) relative to long-dated assets (with differential weights by asset and maturity classes) ([Basel Committee on Banking Supervision, 2014](#)).

Both the LCR and the NSFR are essentially microprudential in nature, since they are calibrated according to individual institutions' liquidity risk, rather than institutions' contribution to systemic illiquidity. From a macroprudential perspective, however, the heterogeneous distribution of contributions to systemic illiquidity across banks could have implications for the optimal cross-sectional distribution of liquid assets. For example, it may be optimal ex-ante to require banks that are systemically important in the interbank network to hold relatively more liquid assets in order to minimise their contribution to systemic illiquidity. This cross-sectional macroprudential approach to calibrating liquidity requirements has been contemplated by policymakers ([Bank for International Settlements, 2010](#); [European Systemic Risk Board, 2014](#); [Clerc, Giovannini, Langfield, Peltonen, Portes & Scheicher, 2016](#)), and has been shown to be effective in theoretical settings by [Perotti & Suarez \(2011\)](#) and [Aldasoro & Faia \(2016\)](#). But we are the first to examine the benefits of a macroprudential approach to liquidity requirements in the framework of a contagion model applied to a real interbank funding network.

The LCR requires that total cash inflows are subject to an aggregate cap of 75% of total expected cash outflows. This requirement may mitigate systemic illiquidity, but only to a limited extent. For example, if a bank has wholesale inflows and outflows of £100 each, it would need to hold at least £25 of LAB. This means that the bank will have enough LAB to survive a stress unless more than 25% of its inflows are defaulted upon. However, when the 75% cap does not bind, as is the case for most major UK banks, the bank only needs to hold enough LAB to cover net outflows, and may become illiquid if some of its expected inflows are not paid on time.

### 5.3 Macroprudential liquidity requirements

To evaluate the usefulness of macroprudential liquidity requirements in reducing systemic illiquidity for a given level of aggregate requirements, we consider the case in which the

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<sup>13</sup> In the EU, implementation of the LCR is phased-in, starting from 60% in October 2015 to 100% in January 2018.

total amount of liquid asset buffers held by all banks in the system is constrained. Such a hard constraint does not exist in practice, but can be interpreted as a threshold above which it would be prohibitively costly for banks to hold additional liquid asset buffers. In this setting, the policy objective is to minimize the proportion of the banking system in default, with the constraint that total holdings of liquid assets are less than or equal to a given quantity.

Formally, in the context of our multi-period model with  $T$  business days, we find the constrained optimal ex-ante distribution of liquid asset buffers that is consistent with the six rules described in [Section 2](#). In such a framework, the constrained-optimal liquid asset buffer  $\mathbf{e}^*$  can be calculated by optimising:

$$\operatorname{argmin}_{\mathbf{e}^*} \sum_{t=1}^T 1 * \mathbf{s}^{*t}(\mathbf{e}) \quad (5.1)$$

subject to

$$\sum_{t=1}^T 1 * \mathbf{e}^{*t} \leq D, \quad \forall j, \forall t,$$

$$p_j^T \leq e_j^T + \sum_{t=1}^T \sum_{i \neq j} p_i^t \Pi_{ij}^t, \quad \forall j, \forall T,$$

$$0 \leq p_j^{*t} \leq p_j^t, \quad \forall j \forall t.$$

where  $\mathbf{s}(\mathbf{e})$  represents the impact score vector calculated in function of the interbank payments in the system, and  $D$  is the constraint on total holdings of liquid assets. This model optimises the ex-ante distribution of liquid asset buffers in a multi-period framework by minimising the proportion of the banking system in default ex-post. For example, the optimal solution might indicate that giving more liquidity to a specific institution (at the expense of others) would be beneficial for overall network stability—as in the stylised case of a bank whose survival is imperative for the overall flow of liquidity within the system.

To see the intuition behind macroprudential liquidity requirements, consider the following. Suppose there are four banks in a network: Bank A, B, C and D. In this toy example, each bank would need a minimum liquid asset buffer of £100 to cover its individual liquidity mismatch over the 22-day period. In aggregate, a minimum of £400 of liquid assets, distributed evenly over the four banks, would be required to avoid illiquidity

ex-post. For illustration, now suppose that the aggregate quantity of liquid assets is constrained at  $D=\pounds 320$ . At least one of the four banks must fail. When network effects are not considered, it is optimal to let the bank with the lowest potential impact score (say Bank B) fail, given that the authority's objective is to minimise the total potential impact score of banks that would fail in the stress scenario. Because Bank B would fail anyway, it is optimal to set Bank B's liquid asset holdings at zero. The other banks would each be required to hold liquid asset buffers of  $\pounds 100$ , with the  $\pounds 20$  surplus distributed arbitrarily. However, when network effects are taken into consideration, the risk of liquidity contagion triggered by bank failures becomes important. Suppose Bank B is a substantial borrower in the interbank network, such that its failure would cause other banks to become illiquid. Then the authority may find it optimal to require Bank B to hold at least  $\pounds 100$  ex-ante, and let another bank risk failure (say Bank C). The constrained-optimal distribution of LAB thus depends on whether network effects are taken into account.

In the context of our model, we use numerical methods to determine the optimal distribution of liquid asset buffers across banks that minimises the proportion of the banking system that would default in the 22-day liquidity stress scenario. That is, we iterate through all possible combinations of LAB distributions across banks subject to the constraint  $D$ , and calculate the total potential impact score of defaulted banks in each case. This procedure is computationally expensive but nevertheless feasible, since the number of possible combinations is finite: in the optimal liquid asset buffer distribution, a bank should hold just enough liquid assets to cover all potential outflows, or no liquid assets at all.<sup>14</sup> Under the macroprudential approach, the constrained-optimal liquid asset buffer distribution is that which minimises the total potential impact score of defaulted banks, taking into account any network effects which generate systemic illiquidity. To evaluate the social usefulness of this macroprudential approach, we compare it to a "microprudential" policy regime which does not take account of network effects in defining the distribution, but which is subject to the same aggregate constraint.

When the interbank network is 300% of its size at the end of 2013 and aggregate liquid assets is constrained at  $\pounds 320$ bn, we find that it is optimal to require a large UK bank to hold zero liquid assets in the constrained-microprudential case without network

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<sup>14</sup> Any excess LAB can then be distributed across banks according to some arbitrary rule (for example, in proportion to banks' constrained-optimal LAB). The distribution of this surplus is irrelevant in the context of our simulation model.

effects. But in the constrained-macroprudential case, when network effects are taken into account, the optimal solution is to require that bank to hold an adequate liquid asset buffer, such that it survives the stress scenario, and instead require two other banks to hold zero liquid assets. In this case, 28.8% of the banking system is in default under the microprudential policy regime which ignores network effects. This reduces to 15.6% when network effects are taken into account under the macroprudential policy regime. The difference reflects the benefit of the macroprudential approach, in which the network effects of systemic illiquidity are taken into account when calculating optimal liquid asset buffers in the cross-section of banks. [Figure 8](#) plots this benefit for a range of liquid asset constraints. The macroprudential benefit is substantial (around 10% on average) when the constraint is between £40bn and £320bn. Beyond £398bn, the constraint is non-binding: the total stock of liquid assets is sufficient for all banks to survive the stress scenario, so that there is no material difference between the two policy regimes.

In summary, a macroprudential calibration of cross-sectional liquidity requirements, taking account of network effects and systemic illiquidity, can unambiguously improve on microprudential requirements. This finding can be interpreted as providing for an efficient re-calibration of microprudential liquidity requirements, in which liquid asset holdings are skewed towards banks that are more important in the interbank funding network.

## 6 Conclusion

This paper studies UK banks' systemic illiquidity using a unique dataset on banks' daily cash flows and short-term interbank funding. We do so through the lens of a model that extends the one-period framework originally proposed by [Eisenberg & Noe \(2001\)](#) to a flexible multi-period interbank payment system.

At the end of 2013, UK banks held historically high levels of liquid assets, and the interbank network had shrunk relative to its pre-crisis size. In this context, our model suggests that systemic illiquidity, conditional on the 30-day stress scenario, is very low. However, when we scale end-2013 liquid assets holdings and the interbank network to mimic their pre-crisis proportions, systemic illiquidity does arise. Furthermore, we identify systemically important banks whose failure would have a significant impact on other banks through liquidity contagion. Banks' systemic importance is weakly correlated with the

size of their interbank lending or borrowing, which suggests that position in the network is a more important determinant of importance.

We also use our model and data to evaluate the optimal calibration of liquidity requirements when holding liquid assets is costly. To do this, we impose a constraint on aggregate liquid asset holdings, and compare systemic illiquidity under two policy regimes: a microprudential regime, which does not take network effects into account when calculating banks' constrained-optimal liquidity requirements; and a macroprudential regime, which takes network effects into account. We find that the macroprudential regime delivers strictly superior results: systemic illiquidity is lower, and a smaller proportion of the banking system consequently fails, for all intermediate constraints on aggregate liquid asset holdings. This result supports the notion that skewing liquidity requirements towards systemically important banks can achieve lower systemic risk at no extra cost.

Our finding regarding the virtues of a macroprudential approach to liquidity requirements has immediate policy relevance. In the European Union, authorities possess some powers within the existing legal framework to implement macroprudential liquidity requirements. According to the capital requirements directive, authorities can impose bank-specific requirements taking into account systemic liquidity risk. These bank-specific requirements can be applied equally to banks with similar risk profiles—delivering a macroprudential overlay to bank-specific Pillar 2 decisions. In future, policymakers could consider elaborating the objective and scope of macroprudential liquidity requirements in EU and domestic law.

Beyond ex-ante policy design, our framework provides a lens through which to identify optimal ex-post intervention. In crisis times, regulators are interested in protecting the financial system as a whole to avoid spill-overs to the real economy. By identifying banks with the largest contributions to systemic illiquidity, our methodology would allow us to find optimal strategies for bail-out or targeted liquidity provision that minimise the cost of ex-post intervention.



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**Table 1:** Summary statistics of the interbank funding network

Day	Mean degree	S.D. of degree	Mean strength (£m)	S.D. of strength (£m)
1	3.28	4.89	233.11	776.95
2	2.63	4.31	68.34	239.08
3	2.18	3.40	59.22	259.35
4	2.52	4.06	91.76	572.27
5	2.61	4.07	63.84	334.50
6	2.41	3.83	51.47	235.19
7	2.55	4.18	49.46	204.45
8	2.40	3.90	45.35	233.72
9	2.35	3.88	27.45	111.25
10	2.48	4.00	48.88	242.85
11	2.76	4.36	28.03	104.32
12	2.27	3.64	22.62	98.22
13	2.59	4.00	25.58	111.85
14	2.36	3.71	18.95	76.15
15	2.40	3.75	17.32	66.83
16	2.43	3.79	20.57	99.26
17	2.08	3.40	28.67	129.92
18	2.23	3.51	18.26	70.14
19	2.50	4.05	21.92	100.21
20	2.25	3.60	19.89	121.81
21	2.31	3.77	34.57	151.63
22	2.31	3.53	12.53	50.84

Note: Table shows summary statistics of standard network metrics for the interbank funding network over the 22 business days of the hypothetical liquidity stress scenario. The metrics are: mean degree, standard deviation of degree, mean strength (also referred to as weighted degree), and standard deviation of strength. The total number of banks in the network is 182.

**Table 2:** Summary statistics of regressors

	Mean	StDev	Min	Median	Max
<i>Impact</i>	0.000547	0.003175	0	0	0.021529
<i>Ownimpact</i>	0.004105	0.015004	0.0	0.000039	0.124050
<i>Betweenness</i>	152.2473	408.7897	0	0	2117
<i>Loginstrength</i>	0.000000005	0.00000003	0	0	0.0000002
<i>InstrengthLAB</i>	0.006528	0.025667	0	0	0.270344
<i>WeightedinstrengthLAB</i>	0.006874	0.031893	0	0	0.341717

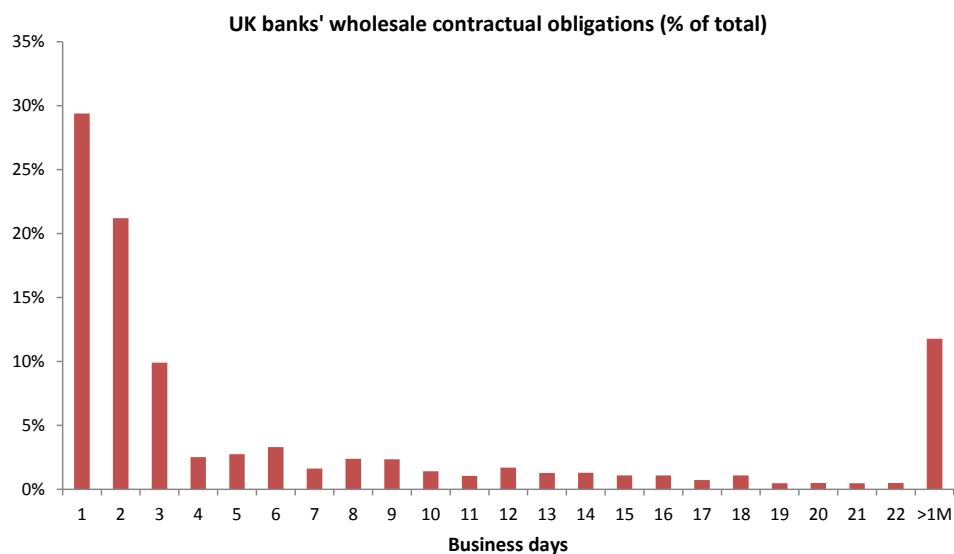
Note: Table shows summary statistics of regressors in [Table 3](#). *Impact* is the dependent variable in [Table 3](#), namely the proportion of the banking system in default following the exogenous default of each bank  $i$ . *Ownimpact* is the impact score of bank  $i$ . *Betweenness* is the betweenness centrality of bank  $i$ . *Loginstrength* is the logarithm of the total borrowing of bank  $i$  from other banks in the network. *InstrengthLAB* for bank  $i$  is defined as  $\sum_j \frac{B_{ij}}{L_j}$ , where  $B_{ij}$  is the borrowing of bank  $i$  from bank  $j$ , and  $L_j$  is the liquid asset holdings (after deducting net flows in the stress scenario) of bank  $j$ . *WeightedinstrengthLAB* for bank  $i$  is defined as  $\sum_j \frac{B_{ij}}{L_j} S_j$ , where  $S_j$  is the impact score of bank  $j$ .

**Table 3:** OLS regression estimation to explain the proportion of the banking system in default following the exogenous default of each bank  $i$

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Ownimpact</i>	0.183*** (0.026)			0.180*** (0.023)	0.175*** (0.022)	0.152*** (0.021)
<i>Betweenness</i>		39.404** (16.004)		8.062 (8.474)	7.776 (8.226)	5.570 (8.280)
<i>Loginstrength</i>			10.962** (4.397)	-3.335** (1.439)	-4.326*** (1.581)	-3.730*** (1.422)
<i>InstrengthLAB</i>					0.011 (0.007)	
<i>WeightedinstrengthLAB</i>						0.021*** (0.008)
$R^2$	0.751	0.257	0.089	0.761	0.768	0.781
$N$	182	182	182	182	182	182

Note: The dependent variable is the additional proportion of the banking system in default following the exogenous default of each bank  $i$ . *Ownimpact* is the impact score of bank  $i$ . *Betweenness* is the betweenness centrality of bank  $i$ . *Loginstrength* is the logarithm of the total borrowing of bank  $i$  from other banks in the network. *InstrengthLAB* for bank  $i$  is defined as  $\sum_j \frac{B_{ij}}{L_j}$ , where  $B_{ij}$  is the borrowing of bank  $i$  from bank  $j$ , and  $L_j$  is the liquid asset holdings (after deducting net flows in the stress scenario) of bank  $j$ . *WeightedinstrengthLAB* for bank  $i$  is defined as  $\sum_j \frac{B_{ij}}{L_j} S_j$ , where  $S_j$  is the impact score of bank  $j$ . Network size is assumed to be 300% of that which prevailed at the end of 2013, and liquid asset holdings are 70% of banks' end-2013 holdings. Standard errors are shown in brackets. \*, \*\* and \*\*\* indicate statistical significance at the 10%, 5% and 1% levels respectively. Constants are estimated but not reported.

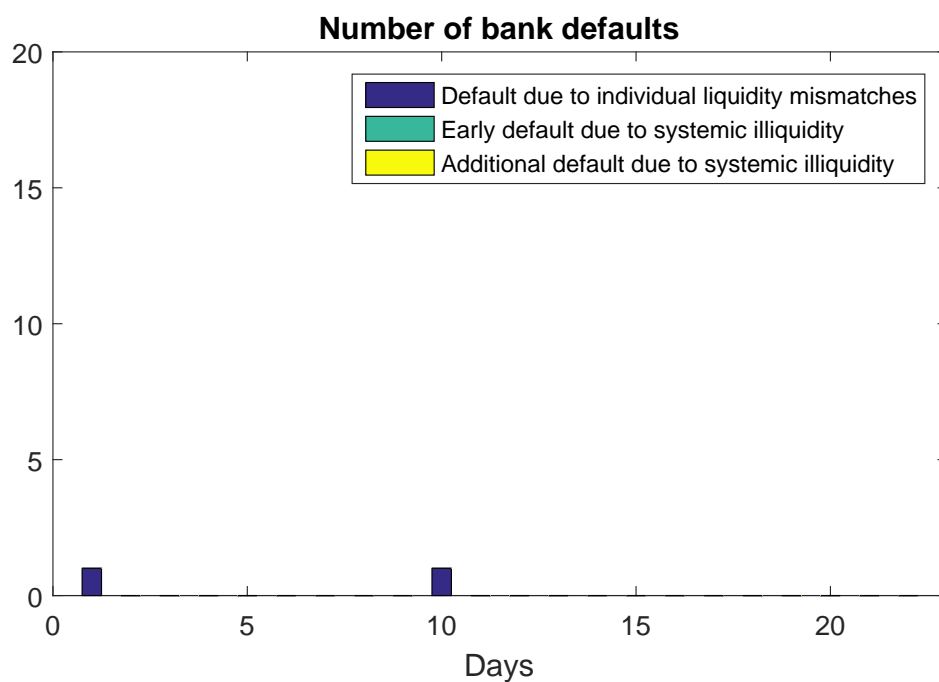
**Figure 1:** UK banks' wholesale contractual obligations by maturity (% of total)



Note: Figure shows UK banks' wholesale funding (as of end-2013) broken down by maturity buckets. The distribution is left skewed as most interbank lending is short-term, including overnight and open maturities. This short-term nature of wholesale funding motivates our focus on illiquidity in the interbank network, since a temporary closure of wholesale funding markets could result in the failure of banks without adequate liquid asset buffers.

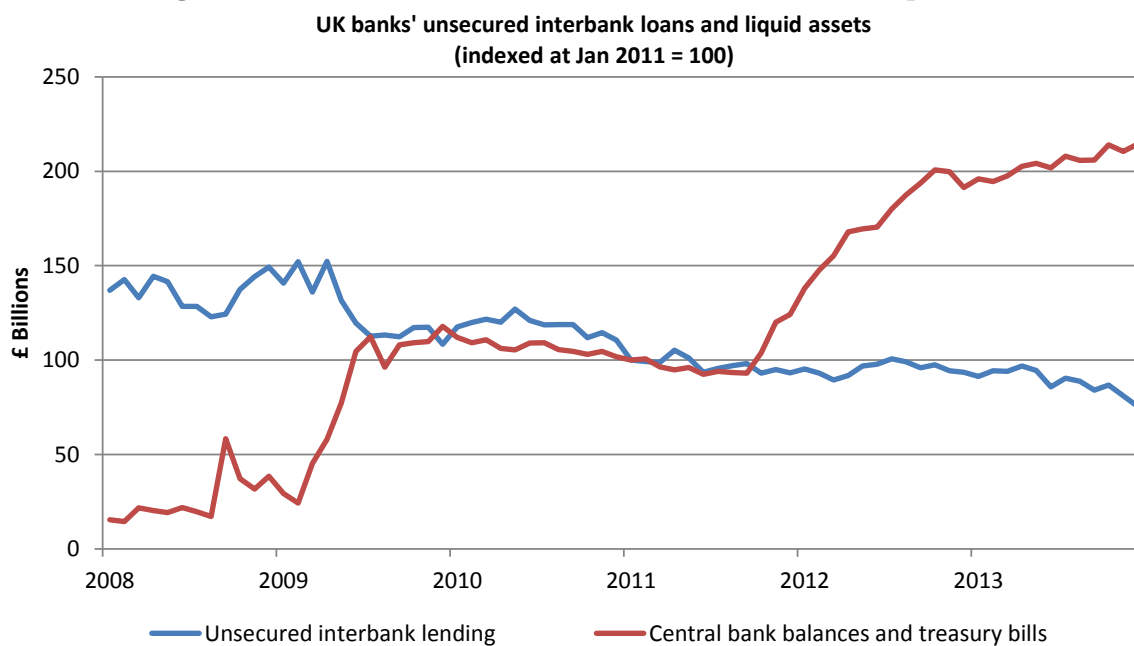


**Figure 2:** Number of bank defaults with end-2013 liquid asset buffer



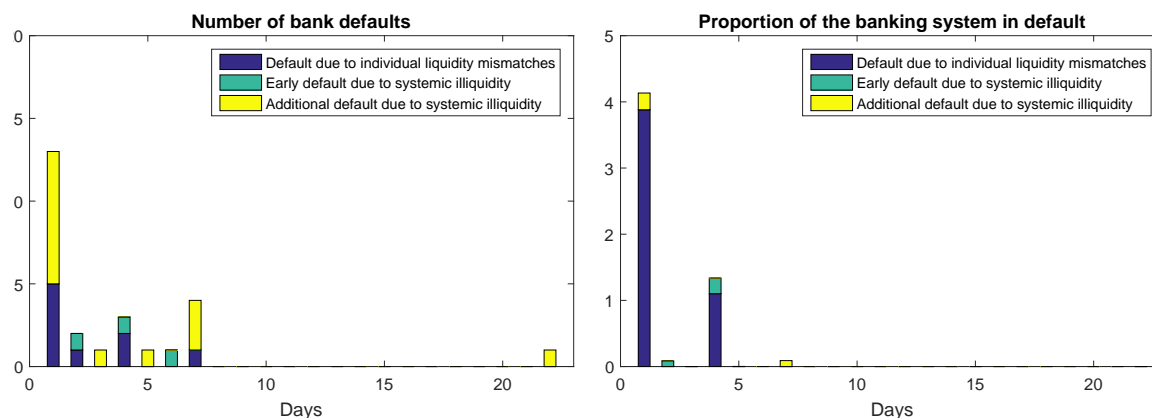
Note: Figure shows the number of bank defaults due to illiquidity in a hypothetical stress scenario in which short-term wholesale funding is not rolled over for a period of 22 business days. In this scenario, and with liquid asset buffers as of end-2013, two banks would default due to illiquidity: one after the first day, and the second after the tenth day of stress. These banks would default due to their own liquidity mismatch, without generating any systemic illiquidity for other banks.

**Figure 3: UK banks' unsecured interbank loans and liquid assets**



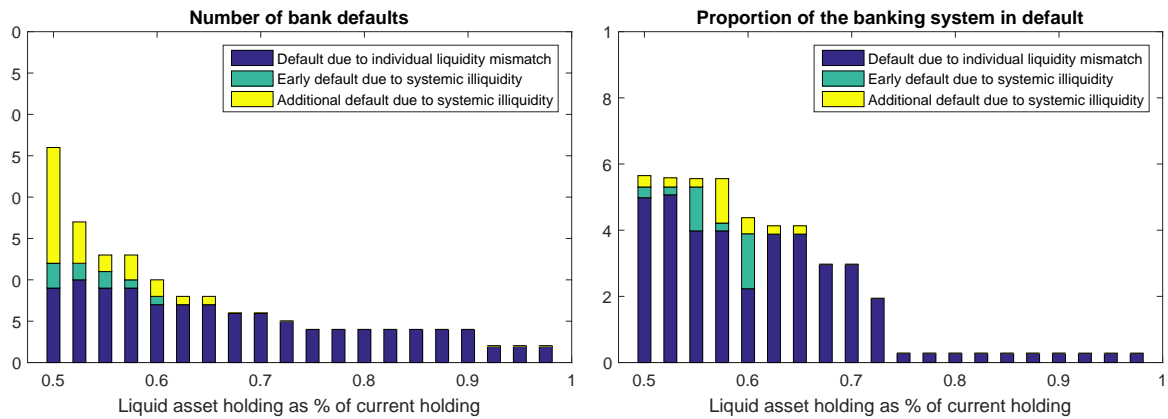
Note: Figure shows UK banks' unsecured lending (blue line, left axis) and holdings of central bank balances and treasury bills (red line, right axis) as of end-2013. The latter slightly understates banks' total high-quality liquid asset holdings because they do not include off-balance sheet holdings. Unsecured interbank lending includes loans in all maturities; it therefore overstates banks' short-term unsecured interbank lending.

**Figure 4:** Bank defaults by day with 50% LAB and 300% network size



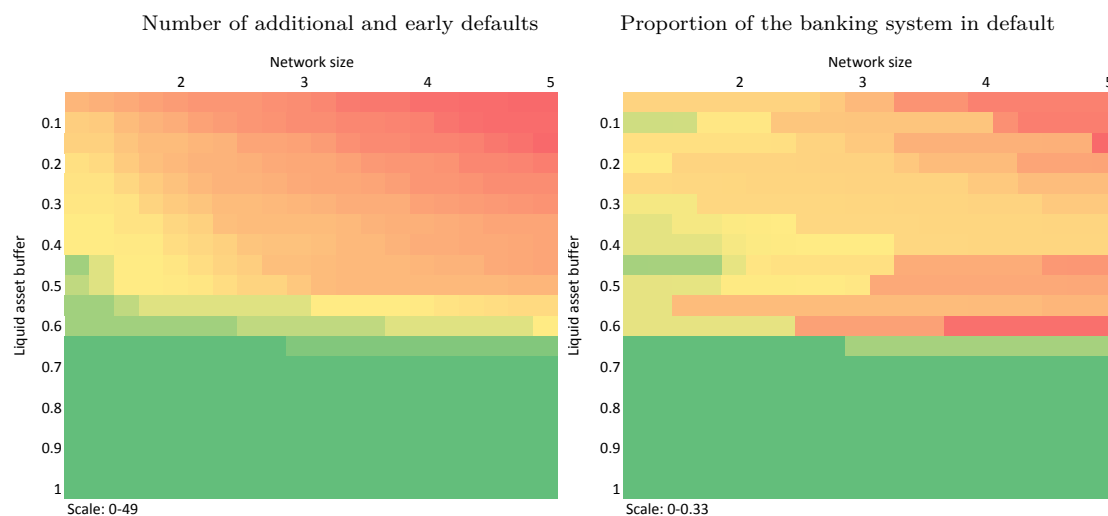
Note: Figure shows the number of bank defaults due to illiquidity (left panel) and the proportion of the banking system in default (right panel) in a hypothetical stress scenario in which short-term wholesale funding is not rolled over for a period of 22 business days. In this scenario, and with liquid asset buffers at 50% of their end-2013 levels and short-term interbank lending at 300% of its end-2013 level, 25 of the 182 sample banks would default. Of these 25 defaulting banks, 9 would default due to individual liquidity mismatch, 3 would default earlier than otherwise due to systemic illiquidity, and 13 would default due to systemic illiquidity (even though they would be individually liquid if other banks had not defaulted). The picture looks different when measuring the proportion of the banking system, rather than the number of banks, in default, as we do in the right panel. Here, we see that the five individually illiquid banks on day one represent nearly 40% of the banking system, and the two individually illiquid banks on day four represent just over 10% of the banking system. These defaults cause an additional c.5% of the banking system to default, or default earlier than otherwise, due to systemic illiquidity.

**Figure 5:** Total bank defaults by LAB with 300% network size



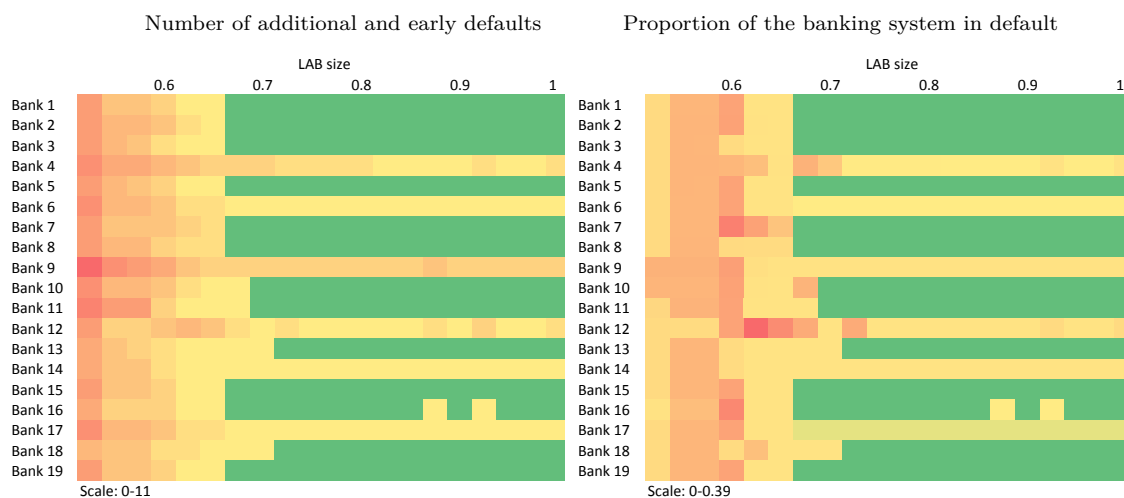
Note: Figure shows the number of bank defaults due to illiquidity (left panel) and the proportion of the banking system in default (right panel) in a hypothetical stress scenario in which short-term wholesale funding is not rolled over for a period of 22 business days. In this scenario, and with short-term interbank lending at 300% of its end-2013 level, the figure plots the number of bank defaults and proportion of the banking system in default as a function of liquid asset holdings. 50% of liquid asset holdings corresponds to the sum of defaults over the 22-day stress horizon depicted in [Figure 4](#).

**Figure 6:** Systemic illiquidity as a function of LAB and network size



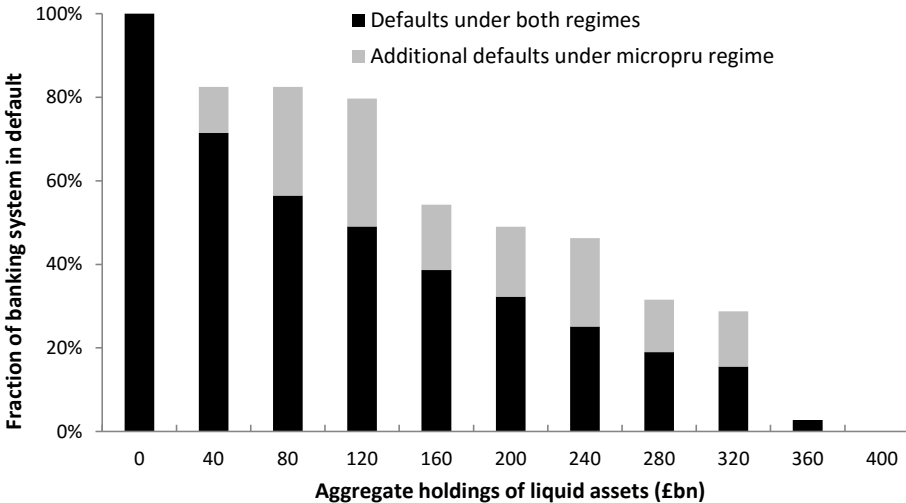
Note: Figure shows the number of bank defaults due to systemic illiquidity (left panel) and the proportion of the banking system in default (right panel) in a hypothetical stress scenario in which short-term wholesale funding is not rolled over for a period of 22 business days. In this scenario, the figure plots the number of bank defaults and proportion of the banking system in default as a function of liquid asset holdings (vertical axis) and size of the network of interbank lending as a multiple of end-2013 network size (horizontal axis). Red/green squares indicate a higher/lower number of early and additional defaults (in the left-hand panel) and proportion of the banking system in default (in the right-hand panel) owing to systemic illiquidity, according to the scale at the bottom of the matrix. For example, a scale of 0-0.33 means that the greenest square has a value of 0 and the reddest square has a value of 0.33.

**Figure 7:** Systemic illiquidity owing to exogenous defaults as a function of LAB



Note: Figure shows the number of bank defaults due to systemic illiquidity (left panel) and the proportion of the banking system in default (right panel) in a hypothetical stress scenario in which short-term wholesale funding is not rolled over for a period of 22 business days, and a given bank exogenously defaults on the first day. In this scenario, the figure plots the number of bank defaults and proportion of the banking system in default as a function of liquid asset holdings (horizontal axis). Red/green squares indicate a higher/lower number of early and additional defaults (in the left-hand panel) and proportion of the banking system in default (in the right-hand panel) owing to systemic illiquidity, according to the scale at the bottom of the matrix. For example, a scale of 0-0.39 means that the greenest square has a value of 0 and the reddest square has a value of 0.39. In this figure, network size is kept at 300% of that which prevailed at the end of 2013.

**Figure 8:** Proportion of banking system in default with microprudential vs macroprudential liquidity requirements



Note: Figure shows the proportion of the banking system in default with microprudential vs macroprudential liquidity requirements as a function of aggregate holdings of liquid assets. The black bar refers to defaults that occur under both microprudential and macroprudential policy regimes. The grey bar refers to additional defaults that occur under the microprudential regime, but which do not occur when liquidity requirements are calibrated macroprudentially. The grey bar can therefore be interpreted as the incremental benefit of the macroprudential approach, which takes systemic illiquidity into account when defining cross-sectional liquidity requirements. In this simulation, the interbank funding network is set at 300% of its end-2013 size.

## Appendix

We use the maximum entropy algorithm to estimate the networks day-by-day. The algorithm estimates all elements of a matrix from the vectors of column-sum and row-sum. The degree of freedom when the algorithm estimates a  $N \times N$  square matrix is  $N \times N - 3N$ , since the diagonal elements of the matrix are known to be zero, and the number of elements to be estimated is  $N \times N - N$ . Therefore the algorithm spreads the elements as evenly as possible to the whole matrix as long as the elements are consistent with the column-sums and the row-sums. Since we use the algorithm to estimate a (number of lenders)  $\times$  (maturities up to a calendar month) matrix, the algorithm tries to spread the liabilities evenly throughout the maturity buckets, as long as these are consistent with the borrowing bank's cash flow schedule.

Günlük-Senesen & Bates (1988) propose an entropy-based bi-proportional technique for estimating a matrix consistent with its exogenously specified row and column totals. In related work, Temurshoev (2012) and Temurshoev, Miller & Bouwmeester (2013) show how to improve this technique for balancing matrices with both positive and negative elements. Let  $A$  and  $X$  be, respectively, the prior and the posterior matrices with their typical elements  $a_{ij}$  and  $x_{ij}$ . Then we define the ratio  $z_{ij} = x_{ij}/a_{ij}$  which should be equal to 1 if  $a_{ij} = 0$ . The optimisation problem is the following:

$$\min_{z_{ij}} \sum_{ij} |a_{ij}| z_{ij} \ln \left( \frac{z_{ij}}{2.71828} \right) \quad (\text{A.1})$$

subject to

$$\sum_j a_{ij} z_{ij} = u_i, \quad \forall i, \quad (\text{A.2})$$

$$\sum_i a_{ij} z_{ij} = v_j, \quad \forall j. \quad (\text{A.3})$$

for a given row and column totals  $u_i$  and  $v_j$ .

Then, we decompose the prior matrix as:

$$A = P - N$$

where  $P$  contains the positive elements of  $A$  and  $N$  contains the absolute values of the negative elements of  $A$ . Then the solution of our optimisation problem is:

$$x_{i,j} = r_i a_{ij} s_j, \quad \forall a_{i,j} \geq 0 \quad (\text{A.4})$$

$$x_{i,j} = r_i^{-1} a_{ij} s_j^{-1}, \quad \forall a_{i,j} \leq 0 \quad (\text{A.5})$$



where  $r_i > 0$  and  $s_j > 0$ . These multipliers are derived from the following quadratic equations, which are obtained by plugging (A.4) and (A.5) into the constraints (A.2) and (A.3):

$$p_i(s)r_i^2 - u_i r_i - n_i(s) = 0, \quad (\text{A.6})$$

$$p_j(r)s_j^2 - v_j s_j - n_j(r) = 0, \quad (\text{A.7})$$

where the coefficients are defined as:

$$p_i(s) = \sum_j p_{ij} s_j \quad (\text{A.8})$$

$$p_j(r) = \sum_i p_{ij} r_i \quad (\text{A.9})$$

$$n_i(s) = \sum_j \frac{n_{ij}}{z_j} \quad (\text{A.10})$$

$$n_j(r) = \sum_i \frac{n_{ij}}{r_i}. \quad (\text{A.11})$$

Assuming that  $p_i(s)$  and  $p_j(r)$  are both equal to  $\theta$ , one may derive the following multipliers:

$$r_i = \begin{cases} \frac{u_i + \sqrt{u_i^2 + 4p_i(s)n_i(s)}}{2p_i(s)} & \text{for } p_i(s) > 0 \\ -\frac{n_i(s)}{u_i} & \text{for } p_i(s) = 0 \end{cases} \quad (\text{A.12})$$

$$s_j = \begin{cases} \frac{v_j + \sqrt{v_j^2 + 4p_j(r)n_j(r)}}{2p_j(r)} & \text{for } p_j(s) > 0 \\ -\frac{n_j(s)}{v_j} & \text{for } p_j(s) = 0 \end{cases} \quad (\text{A.13})$$

One of the attractive features of the maximum entropy algorithm is the availability of its analytical solution that can be easily used in an iterative procedure. Therefore, there is no need to use high-performance computers to estimate the matrix of liabilities for each bank day-by-day represented by  $X$ .