A Data Rich Money Market Model
Agent-based Modelling for Financial Stability

Paul Devine and Rahul Savani
Dept. of Computer Science, University of Liverpool, Liverpool, L69 3BX, UK

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Abstract: Our position is that agent-based modelling is a potentially powerful complementary tool in the study of financial systems, especially where institutional behavioural factors and empirical data are incorporated. The work reported here concerns an agent-based model of a banking system focused on liquidity provision, principally the flows of cash between banks and other system actors. This model has been developed in conjunction with senior staff drawn from a major UK bank and consultancy and is highly data-rich in comparison with previous theoretical work in the field. Agents and relationships reflect practitioners' views of the system and it incorporates institutional balance sheet representations, financial instruments together with real-world data collated from a range of sources. The bank agents in the model possess heterogeneous behaviours and data content drawn from real bank data. We report preliminary studies of the dynamical behaviour of this system in the context of the types of systemic shocks and perturbations observed in the real world. We review results which model the impact on a bank of a perceived lowering of its creditworthiness. These dynamics are not the result of endogenous assessments of the bank's position, but the interplay of other banks' and actor's responses with its own behaviour.

1 INTRODUCTION

Our contention is that data-rich agent-based models can become a valuable component of the toolkit available for analysis of financial systems. The financial system is comprised of a large number of actors, financial instruments and relationships and is a considerable challenge to both model and regulate. This challenge has become more urgent since the subprime crisis of 2008 which precipitated substantial state intervention to shore up the system. A feature of that crisis was the evaporation of the interbank money market, the system by which liquidity (cash) is accessed by banks to meet their immediate needs. Traditionally, theoretical system models are high level and use macro-economic techniques, while at the institutional, real-world level a large amount of financial and balance sheet data may be analysed.

To this end, we have taken an intermediate approach, developing an agent-based model to simulate the system actors and their interactions with a particular emphasis on the provision of liquidity. This facilitates individual behaviour to be explicitly modelled and the individual corporate actors in the system differentiated by this behaviour and their state data.

It has been argued that the crisis exposed the limitations of traditional approaches, and that agent-based models may be essential to building effective models of the economy to address these shortcomings (Farmer and Foley, 2009). The promise of applying agent-based models to the economy had already been noted in the context of the shortcomings of approaches that assume homogeneity or weak heterogeneity (Gallegati et al., 2003). Subsequently, agent-based models have been applied to areas of the system including housing (Geanakoplos et al., 2012) and its contribution to systemic risk. We concur with this and believe that no single paradigm is adequate for a sufficient understanding of the system. Macro approaches such as Dynamic General Stochastic Equilibrium (DGSE) models describe the system in a relatively stable state, not the unstable systemic dynamics that often occur under stress or at the periphery of this region. Traditional models of financial systems and stability used by banks, central banks and regulatory bodies are typically highly data intensive, concentrating on the systematic evaluation of balance sheets and known exposures. For example, the Bank of England employs the RAMSI stress testing framework (Burrows et al., 2012) which entails the collection and

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processing of a wide range of publicly available data together with regulatory data submitted in confidence by the banks. The goal of RAMSI is to identify potential deficiencies or weaknesses in a specific part of the system. In stark contrast are theoretical models of contagion, e.g. the seminal work by Allen and Gale (Allen and Gale, 2000) where liquidity is modelled as an equilibrium process with counterparty risk acting to spread contagion. These examine mechanisms and structures in a manner that could not be further removed from bankers' balance sheets, financial instruments and day-to-day activities. The underlying technical infrastructure of centrally cleared interbank cash flows, Real Time Gross Settlement Systems (RTGS), has also been investigated from an agent-based perspective, in modelling (Biancotti et al., 2009), design and operational (Galbiati and Soramki, 2011) contexts. Our agent-based approach is intended to capture some elements of all.

2 THE TARGET DOMAIN

Money Markets are central to the effective operation of the financial system and were first analysed in the 19th century (Bagehot, 1873) when the London market was pre-eminent. In fact, banking crises and financial bubbles long predated this, having been a problem in ancient Rome (Thornton and Thornton, 1990), as was the formulation of effective regulation. The market consists of a highly heterogeneous set of actors, complex interactions and a lack of clarity in overall exposures, largely due to the opacity of counterparty risk. In terms of investigating liquidity risk as a systemic threat, endogenous cycle and macro stress testing models tend to have little behavioural content, though post-crisis analysis has highlighted the behavioural factor in events (van den End and Tabbae, 2012). It has been hypothesised that the overnight market freeze of August 2007 was due to the adoption of precautionary behaviours (Acharya and Merrouche, 2012). Crucially, the potential for crisis does not appear to have receded, the Chinese interbank market froze in 2013 with interbank rates peaking at 25% (Economist, 2013).

Interbank liquidity is essential for the smooth operation of banking, banks rely on the availability of cash and highly liquid assets to meet their obligations to clients and to engage in financial transactions. Requirements may vary greatly during any given time period, with extremely large volumes of cash typically flowing both into and out of banks on a daily basis. This is driven by trading activities in equities, bonds and foreign exchange markets, together with the needs of customers to make commercial and personal payments. The potential for contagion through these linkages has long been recognised and has been the subject of theoretical investigation and close practical scrutiny. A significant illustration of the centrality of interbank liquidity occurred during the 2008 sub-prime crisis where institutions (e.g. Bear Stearns) failed not as a result of insolvency, where total liabilities exceed assets, but of illiquidity due to inability to meet immediate liquidity requirements despite apparently sound underlying balance sheets.

3 THE MODEL AND AGENTS

The core assumptions on which the liquidity model is based were identified in collaboration with banking professionals. The principal actors are: banks; customers; the central bank; cash rich entities(CREs). Cash and liquidity flows across the system between individual banks and CREs with the central bank as the final resort for liquidity. Customers represent the real economy, withdrawing and depositing liquidity to and from the system. The following five agent classes were developed to represent principal actors, complemented by a financial instrument type (contract) to encapsulate the exposures and relationships between market members.

Banks are the principal actors with the system. Each bank contains a unique balance sheet, described in Table 1, together with sample data used in the initial evaluation of the simulation.

Table 1: Bank Balance Sheet.

Assets	£m
Cash and Reserves	68,487
Loans to Banks	97,140
Loans to Customers	489,399
Highly Liquid Assets (Bonds)	71,392
Illiquid Assets	706,363
Liabilities	£m
Deposits from Banks	109,097
Deposits from Customers	472,388
Other liabilities	851,296
Equity	61,964

The balance sheet structure reflects its centrality to practitioners' perspectives on the market and incorporates features considered most salient for the proposed work. Additional to this, a bank agent also contains state information for risk appetite (*ra*) and creditworthiness (*cds*) together with a full expression of the bank's assets and liabilities with respect to each of the other banks and its known position at future points. At any simulated day, d, a bank contains data that details: total cash owed; total cash owing; cash owed (by institution); debts due at $d+n$; credits due at $d+n$. In tandem with the balance sheet data this information is available to be used in defining complex, differentiating behaviors across banking agents. The information can also be used to evaluate the banks' states in relation to proposed regulatory measures like the Liquidity Coverage Ratio (*LCR*) (BIS, 2013) and Net Stable Funding Ratio (*NSFR*) (BIS, 2014), proposed under the Basel III regulatory regime designed in response to the events of 2008.

Cash Rich Entities represent non-bank sources of liquidity, for example corporations or money market funds. Since the market for interbank liquidity became moribund in the aftermath of the sub-prime crisis, UK Banks have become more reliant on what they refer to as Cash Rich Entities (CREs) for the provision of liquidity. The rise of the non-Bank Financial Institutions (NBFIs) and Other Financial Institutions (OFIs) has resulted in them being of great systemic importance, a European Commissions study indicated that their assets in the EU27 totalled €32.6tn in 2011, exceeding those held by MFIs by c.50 % (EC, 2012). Though used solely as potential sources of liquidity in the preliminary work reported here, CREs have been included not only due to their size, but also because some are becoming increasingly important in Shadow Banking.

The **Central Bank** (in the UK, the Bank of England) is the lender of last resort and setter of interest rates, it both participates in and, to some extent, makes the market. The lender of last resort role, where a the Central Bank acts as a source of liquidity, can operate to smooth out inefficiencies in the market (Matsuoka, 2012). However, in the aftermath of Lehmann Brothers' collapse in 2008 Central Banks intervened in what were considered non-standard ways (Giannone et al., 2012), with banks being propped up due to systemic importance, "To Big to Fail" (TBTF) . Concerns with respect to the potential market distortions and moral hazard engendered by TBTF are not new, Herbert Spencer, a nineteenth century contemporary of Bagehot, argued "the ultimate result of shielding man from the effects of folly is to people the world with fools", a remark specifically aimed at this activity (Kindleberger, 1996), a sentiment that has been revisited with vigour post-2008. Nevertheless, central banks on both national and supranational levels are essential components of the financial system. Their policies are vital instruments of market and regulatory control and they can be conduits of state intervention. Cross-country econometric analysis has indicated that the fiscal cost of state and central bank support in crisis situations may exceed 50 % of GDP (Honohan and Klingebiel, 2003). Like a real central bank, the central bank agent sets the central bank interest rates and acts as a source of liquidity.

Customers, retail and commercial, help drive banks' day-to-day liquidity activities which are heavily informed by movements in deposits and withdrawals. Though largely known in advance, there are significant, unpredictable fluctuations which may stress the institution's liquidity position and a trend towards heavy withdrawals may cause catastrophic stress, ultimately leading to failure in the absence of external intervention to shore up liquidity. This happened with Northern Rock in the UK. Customers have been incorporated in the form of customer agents that provides aggregated withdrawal and deposit activity for corresponding bank agents.

Financial Instruments are incorporated into the model as *Contracts*, illustrated in 1.

$$C = (p, r, d, m, t, l, b, y) \tag{1}$$

The terms represent: p, principal, the amount loaned; r, the rate of interest; d, the date of inception; m, the time of maturity; t, the term of the loan (duration); l, the identity of the lender; b, the identity of the borrower; y, the yield (expected profit) of the contract. Contracts are used to build up interbank positions over four term lengths: overnight; one month; three months; six months.

4 AGENT RELATIONSHIPS

Each bank has transaction relationships with a specific customer agent, a set of CREs, the central bank and all other banks, or a subset. A subset in this context represents preferential relationships, these may exist in the market and evidence suggests that they persisted through the 2008 crisis, facilitating the support of badly affected banks (Affinito, 2012) thus mitigating contagion. Transactions with customer agents are straightforward withdrawals and deposits, those with all other agents involve negotiation and the creation of a Contract, Contracts are then settled when their terms are reached. The relationship networks provide the routes via which stress and contagion may propagate through the system.

5 IMPLEMENTATION

The model has been developed on the Repast Simphony platform after investigating other options

(Railsback et al., 2006) and Java selected for the implementation. Reasons for this selection include the relative maturity of the platform, well developed libraries and data handling facilities.

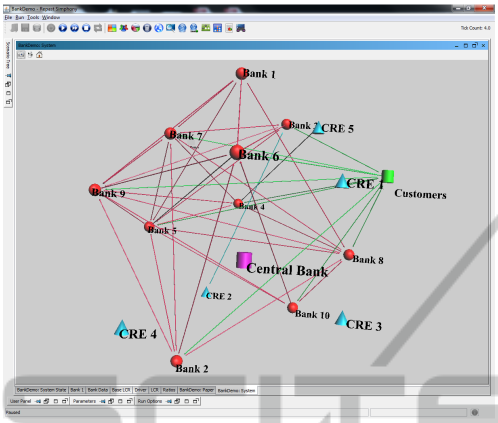

Figure 1: Screen shot of the simulation.

The simulation is illustrated in figure 1 where the evolution of the transaction network may be observed and individual agents interrogated for their state variables. Scenarios and outputs may also be specified and data collected for post simulation analysis. For display purposes the customer agents have been aggregated into a single visual representation.

5.1 Data Population

Data availability and consolidation is a challenging issue, there exist both famine and feast in terms of the the publicly available data. Banks' annual and quarterly reports contain a wealth of data, typically running into hundreds of pages, this is far in excess of requirements at this formative stage of the project. However, quarterly and annual report balance sheets only contain snapshots of a bank's state, detail between the reporting periods is lost and the most interesting features may not be widely known outside the banks. Similarly, details of interbank exposures are not publicly available.

Banks' Balance Sheets were initialised from a variety of sources, principally the institutions own published consolidated balance sheets for the period covering 2011 onwards. This was supplemented by data obtained from Bureau Van Dijk's BankScope product, this makes balance sheet data available for all a banks in Fitch's uniform format.

Two further sources of data were utilised for setting up banks' initial states, and potentially drive behaviour during runs of the simulation. Credit Default Swap (CDS) pricing, a proxy measure of an institution's creditworthiness was gathered in the form of daily prices for each bank corresponding the to balance data. During each run the CDS value within in each bank may be adjusted in accordance with historical data, or recalculated as required by simulation scenarios or outcomes. The second data requirement was for a means of initialising rates in the financial instruments, a realistic baseline being required. For this the now somewhat discredited LIBOR data set was used. LIBOR was a daily statement of interbank rates over a range of terms and currencies collated from the banks' own submissions to the British Banking Authority. It has been demonstrated that there were attempts by some participating banks to manipulate the published rates, this renders the data commercially unreliable. However, extremely accurate data was not required for our purposes and the magnitude of the attempted manipulation was well within our requirements.

Customer Transaction data were not readily available. In the absence of real day-to-day transaction data from the banks we approximated deposit/withdrawal behaviour from publicly available data. Sources used included: Bank of England; BBA; UK Cards Association. The data was used to prime the activities of the customer agents, scaled in accordance with their relative balance sheet sizes and then subjected to a random positive or negative offset to replicate the unpredictable component of daily transactions. The customer agents may be further manipulated to replicate customer withdrawal stress or excess liquidity.

5.2 Model Operation

In its general form the model contains n banks, m CREs, 1 central bank and x customer agents. It has a flexible, discrete time-step form with the highest real data resolution at the day level. For simplicity, in the work presented here a time step is the equivalent to a day. However, a facility to run multiple steps per day was included to allow simulation of intra-day interactions if necessary. In the reported form the simulation is bank-centric. All banks are processed each step but randomly chosen to avoid introducing ordering artefacts in the output data. For bank B_n the behaviour suite, i.e. activities it may initiate each step t, are as follows:

- B_n receives withdrawal or deposit from customer agent C_n and updates balance sheet
- If B_n is solvent the bank is frozen
- Calculate liquidity required to cover obligations and satisfy LCR

- Settle financial instruments due this step, updating accordingly
- Buy highly liquid assets (bonds) if cash supply allows
- Approach CREs for liquidity
- Poll other banks to borrow liquidity (may be routed through broker agent) for outstanding liquidity requirement
- Approach Central Bank if liquidity requirements not met
- If liquidity requirements are not met, sell liquid assets at balance sheet value
- If liquidity requirements are not met, sell illiquid assets at discount (fire sale)

Each time step bank m may assess requests for loans submitted by other other banks, these requests are made in the form of a contract c. The lending decision behaviour is governed by the function in 2.

$$f(LP_m, CDS_n, r_c, y_c, t_c) \quad (2)$$

Where LP is the liquidity position of bank m; CDS_n the creditworthiness of bank n; r the rate of c; y the yield of c and t the term of c. Bank m may accept, reject or modify the terms of c, in the event of modification a revised contract c' is returned to bank n for acceptance or rejection, no further negotiation being entered into between n and m. In the preliminary investigation, subject to LP_m, contracts were assessed on the basis of CDS_n, r_c and y_c, weighted in that order. More complex behaviours will be the subject of future work and should be developed in conjunction with industry expertise. Stress may be applied system-wide, to a single bank or a subset of banks. Potential sources of stress are: Customers, nett withdrawals; *CDS* values, the creditworthiness of the bank; Devaluation of illiquid assets; General system confidence.

5.3 Model Behaviour, a Credit Example

In common with many models of complex systems this one can be highly sensitive to initial conditions and initial work has concentrate on qualitative behoviours. The example is illustrative of the type of realistic qualitative behaviour the model exhibits. Two scenarios are compared in Figure 2, the plots are for a single bank within the system, not an aggregated view, and cover a period of 800 working days.

Blue represents *business as usual*, for red all data is the same except for stress applied to *CDS* spread of one bank in the ten, effectively lowering its creditworthiness for a period. For blue, the Banks' *CDS* spread are set from corresponding real data and the balance

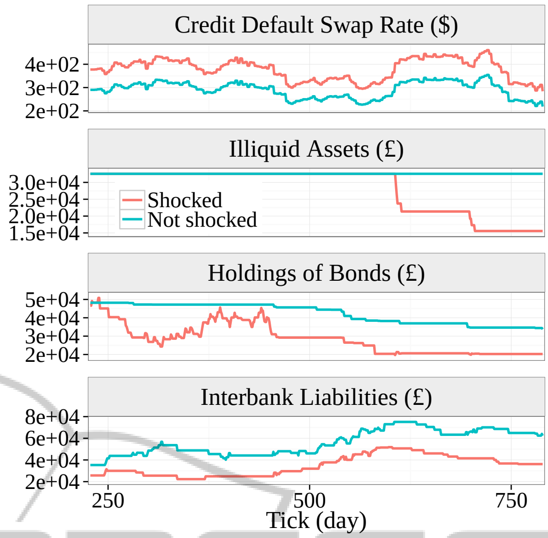

Figure 2: Normal vs. depressed bank creditworthiness.

sheets initialised from real banks' consolidated balance sheets. Customer agent deposits decline over this period, providing a mild reduction in day to day liquidity. The graphs show the bank's activity on the interbank market to meet liquidity requirements, together with a gradual sale of highly liquid assets (Bonds) where required. The bank's illiquid assets remain untouched. In the red plot the bank's *CDS* value is inflated to simulate a perception of relatively poor creditworthiness in the market. The first consequence is the difficulty in securing liquidity on the interbank market, illustrated by the depressed interbank liabilities graph. To compensate, bonds are sold in order to stave off illiquidity, a clear difference between the stressed and unstressed scenarios. Eventually the bank is forced to sell its illiquid assets at a heavily discounted price, an asset firesale. For this scenario, the customer agent acted merely as a source of withdrawals and deposits. Were more complex customer behaviours to be incorporated we would expect to see heavy withdrawals as confidence in the bank erodes.

6 NEXT STEPS

We believe the current work to be promising with qualitatively realistic dynamic behaviour observed in the model. The immediate focus should now be on drawing these closer to reality with a greater degree of quantitative rigour. The wealth of data in the simulation has yet to be full exploited, and it should be noted that this level of complexity is a source of both potential weakness and strength, especially in respect of sensitivity to initial conditions. Next steps will entail restricting data and behavoiurs to provide a more tractable simulation with a more managable parameter space, it is envisaged that scenarios simulating a range of bank behaviours under idealised regulatory regimes (e.g. Basel III) would be a logical next step, hence the inclusion of LCR.

7 CONCLUSIONS

Ideally, an agent-based model may encapsulates expert knowledge, actor behaviours and system structure in a manner that eludes other techniques. The model described here does not share the clean and often elegant characteristics of a classical, analytical model, but then the real world does not share these features either. Neither does it posses the rich detail of institutions' financial positions, covering hundreds of pages of their annual reports, one of the experts commented that there is no simple representation of a £1.4tn balance sheet. Our model does capture behaviours, structure and expert knowledge and includes some of the data richness of the real world. The most important outcome of the initial simulations, like the creditworthiness example described here, is that they demonstrate that the model is an interacting set of institutions rather than merely single entities or an aggregation of many. For example, the effect of diminished creditworthiness on a bank was a combination of the behavioural responses of the other agents and its own response to those actions, all occurring within the context of a realistic structure with real data. These features are particularly suitable for analysing crisis scenarios or testing the impact of regulation where behavioural responses can dictate outcomes.

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