The Concerted Run on the DSB Bank: An Exploratory System Dynamics Approach

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Abstract

In this paper, an Exploratory System Dynamics model of a concerted run is first of all presented. The immediate cause for modelling a concerted bank run was the mediatised call for a run on the DSB bank. This Exploratory System Dynamics model was developed the morning of the call for the bank run, before the start of the ensuing bank crisis, in order to quickly foster understanding of possible dynamic behaviours of 'concerted' bank runs and to perform rough-cut policy/strategy analyses. The model is subsequently used to illustrate the combination of Exploratory System Dynamics modelling and Exploratory Modelling and Analysis, or Exploratory System Dynamics Modelling and Analysis.
The paper starts with a short overview of the DSB Bank crisis, the description of the exploratory System Dynamics model and some quick exploratory analyses. The model is then used as a scenario generator for Exploratory System Dynamics Modelling and Analysis in order to analyse and deal with deep uncertainties surrounding the issue and its modelling (parameters and functions). The paper ends with some applied conclusions and policy recommendations, methodological conclusions, and venues for future work.

Keywords: Bank Run, DSB Bank, SD, EMA, ESDMA, Exploratory System Dynamics Modelling and Analysis

1 Introduction

1.1 The Issue: The Abbreviated Story of a Concerted Bank Run

The immediate cause for the development of the model presented/used in this paper, was the call on the morning of 1 October 2009, broadcasted on Dutch television, for a run on the DSB bank[1].

The DSB Bank –the Dirk Scheringa Beheer Bank– was a very special case in the Dutch financial landscape: the relatively small DSB bank was founded and owned by Dirk Scheringa, a former policy agent and self-made banker, who held the limelight as main sponsor of the Dutch soccer club AZ, the DSB speed skating team, and a museum of realist art. Being a popular figure head and claiming that his bank was untouched by the 2008-2009 economic crisis, he even suggested becoming crisis minister to steer the Netherlands out of the economic crisis.

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[1] For a detailed reconstruction of the 'DSB story', see the official report of the Scheltema Commission (Scheltema, Graafsma, Koedijk, du Perron, et al. 2010) available on `www.commissiedsbbank.nl`. The 'Scheltema Report' and many of the details revealed in it were not available at the time of modelling and writing.

However, his bank also became rather infamous for some of its lending practices which measured up to American sub-prime lending practices. In this case, the scam[2] involved usury single premium insurance policies[3] (in Dutch: '*woekerkoopsompolissen*') with low starting interest rates for luring customers, but with exorbitant commissions (51% according to DSB but 80-90% according to other sources) that were added to the principal, resulting in mortgages far above execution values (on average 146%) and –once the luring interest rates were raised– far above debtors' abilities to pay the interests, not to mention their abilities to repay the principal. Many debtors were –soon after borrowing– unable to (re)pay their loans and many of them could not refinance their disproportionably high mortgages nor sell their homes without ending up with large residual debts.

The DSB Bank and its umbrella holding were under surveillance by the financial authorities for insufficient disclosure of information, conditional sale (which is actually forbidden), exceeding on overdraft facilities, intransparent financing between subsidiaries, etc.

In the months preceding the concerted bank run, angry debtors and organisations representing them were able to get media attention regarding their grievances, damaging the Bank's reputation. Additionally, many Dutch savers experienced hindrance from other bank failures and –although most of them got all their money back– the hindrance these bank failures caused also received media coverage, raising Dutch awareness of bank failure risks beyond the deposit guarantee[4].

Then on the morning of 1 October 2009, Pieter Lakeman, a lawyer claiming to represent a group of angry clients who were in financial problems because of buying financial products from DSB, called all depositors –on Dutch public television– to join for a run on the bank. Thousands of depositors followed Lakeman's call, and emptied their liquid deposits. On 1 and 2 October, the average outflow amounted to €90 million, followed by more than €120 million on 3 October, and an average of €50 million on each of the following 5 days. Although by 11 October the outflow had practically stopped, the bank was severely affected by a cumulative outflow of €664 million in less than 2 weeks.

Behind the screens, De Nederlandsche Bank (DNB), the Dutch central bank, contacted all major Dutch banks in an attempt to set up a rescue operation. On 11 October, the negotiations with the major Dutch banks to rescue DSB via a take-over by these banks failed after they requested an unlimited guarantee (possibly amounting up to €5 billion) from the Ministry of Finance, which the Ministry refused. Other plans failed too. That Sunday evening, DNB asked the court for an 'emergency measure' ('*noodmaatregel*') in order to place the DSB Bank under legal restraint. That evening, the DSB Bank was still judged sufficiently solvent and liquid. But that same night, leaks/rumours about the failed rescue operation caused an early-morning panick and second run on the bank (of about €30 million between 5.30am and 11.30am), because of which DNB asked the court once more for an emergency measure. This time, DSB Bank was placed under legal restraint. Being made a ward of court, Scheringa tried to save his bank but failed. On 19 October 2009 an adjudication order was issued: the bank went bankrupt, unseating Scheringa's imperium.

Although it is estimated that –after deducting the costs of the compulsory liquidation– 96% –or €4.07 billion of the €4.24 billion– of all outstanding claims will be refunded, and the savings guarantee reduces much of the damage for most depositors, the concerted bank run made a lot of victims: 1400 employees immediately lost their jobs, about 4500 clients with subordinated deposits will most likely lose all deposits, about 4000 clients with deposits exceeding the savings guarantee may lose that part of their deposits, the other deposit banks are forced to finance the uncovered part of guaranteed deposits, and Dirk Scheringa lost his bank and holdings, museum and art collection, as well as his soccer club and skate team. And Lakeman's clients... will most likely be among the losers too.

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[2]It should be noted though that the DSB Bank was not the only financial institution in the Netherlands to sell such financial products.

[3]A single premium insurance policy is an insurance policy that is sold in combination with a consumptive credit or a mortgage, and for which the full insurance premium needs to be paid upfront and is financed by inclusion in the consumptive credit or mortgage itself.

[4]Up to €100000 of deposits per person per bank are covered by the deposit guarantee system.

1.2 Exploratory System Dynamics, Exploratory Modelling and Analysis, and Exploratory System Dynamics Modelling and Analysis

System Dynamics (SD) (Forrester 1968) (Meadows and Robinson 1985) (Sterman 2000) is traditionally used for modelling and simulating dynamically complex issues and analysing their resulting non-linear behaviours over time in order to develop and test effectiveness and robustness of structural policies (see appendix A on page 22 for an introduction to SD).

The traditional SD approach may have to be turned into an exploratory approach for *deeply uncertain issues*. Deep uncertainty is defined by Lempert, Popper, and Bankes (2003) as situations

> 'where analysts do not know, or the parties to a decision cannot agree on: (i) the appropriate conceptual models that describe the relationships among the key driving forces that will shape the long-term future [e.g. different drivers and underlying structures than today], (ii) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (iii) how to value the desirability of alternative outcomes.'

Improving models by increasing the level of detail or their size does not seem to help much for such issues. Instead of trying to develop ever more detailed models validated on past conditions, it may be more useful to focus on

- quickly exploring plausible behaviours with a relatively simple model –or relatively simple models– without aiming to uncover *the* structures underlying the real issue and forecasting *the* behaviour or *exact probabilities* of precise behaviours or the real issue;
- exploring and analysing the entire space of plausible behaviours that can be generated by large uncertainty ranges for all uncertain parameters and structurally uncertain model formulations; and
- exploring and analysing the (relative) effectiveness and robustness of policies given all sorts of parametric and structural uncertainties, in other words, in the face of deep uncertainty.

More exploratory SD modelling, use and interpretation may be very useful for the first bullet, and Exploratory System Dynamics Modelling and Analysis –a combination of Exploratory System Dynamics and Exploratory Modelling and Analysis– may be very useful for the second and third bullet.

Exploratory System Dynamics (ESD) refers to the use of fast-to-build, relatively-small, highly-simplified, data-poor, easy-to-use SD models to quickly/easily explore possible behaviours and plausible scenarios, and develop a rough idea about the effectiveness and robustness of policies (Pruyt 2010d). The focus of ESD lies on testing whether behaviours of interest (e.g. plausible trajectories that require attention) can be generated (at all), and exploration of plausible types of behaviours. Scenario analyses, risk analyses and what-if analyses are used in ESD, but in a slightly different way, with a very different interpretation, and for a very different goal than traditionally, because the issues for which ESD is useful are just too uncertain and the ESD models developed just too wrong[5] (but also more useful for the purpose of exploration). In ESD, it does not make sense to derive firm conclusions about specific values or sets of conditions that may lead to this or that behaviour, or to interpret outcomes in a probabilistic sense. Hence, ESD may be good as an introduction to dealing with complex and uncertain issues, it is not useful for detailed analysis in view of detailed implementation or to totally reduce uncertainties, and more importantly, ESD on its own may not be sufficiently systematic for well-founded decision support for issues characterised by deep uncertainty.

Exploratory Modelling and Analysis (EMA) (Agusdinata 2008) (Lempert, Popper, and Bankes 2003) allows generating insights and understanding about the functioning of systems and the effectiveness and robustness of policies, while taking complexities and uncertainties seriously into

[5] All models are wrong, but some are just more useful (Sterman 2002).

account. It consists of using exploratory models for generating an ensemble of future worlds (tens of thousands of scenarios) in order to test the effectiveness and robustness of policy options across the ensemble of future worlds. The question for EMA is not 'when to measure more' nor 'when to model better', but 'how to explore and analyse under deep uncertainty in order to design policies that effectively and robustly improve the system/behaviour given the deep uncertainty'.

Since EMA requires handy models to generate thousands of plausible scenarios (future states), and ESD requires methods to systematically explore deep uncertainty, they are actually natural complementary allies (Pruyt 2007) and can be combined into Exploratory System Dynamics Modelling and Analysis (ESDMA). ESDMA consists of (i) developing (one or) several ESD models regarding an uncertain issue, (ii) simulating them with extended ranges of parametric uncertainty and different structures/formulations, (iii) analysing the resulting dynamic behaviours and bifurcations given the structural and parametric uncertainties, and (iv) testing the effectiveness and robustness of policy options given these and other uncertainties. In other words, the Exploratory SD models are thus used as scenario generators for the Exploratory Modelling and Analyses in order to explore deeply uncertain issues and support decision-making under deep uncertainty. Practical tools to ease the combination of ESD and EMA are currently under development at Delft University of Technology. A simple example of ESDMA is provided in section 4 and typical outputs are attached in appendix C. Other examples are discussed in (Pruyt 2010d), (Pruyt and Hamarat 2010), and (Pruyt 2010c).

1.3 Goal and Organisation

1.3.1 Goals

The three main goals of this paper are to:

- explain the use of ESD for its own sake, in other words, without combining it with EMA;
- explain the use of ESDMA – the combination of ESD and EMA;
- illustrate the application of ESD and ESDMA on a relatively simple example, namely the concerted run on the DSB Bank, and hence, shed light on the dynamic complexity of potentially concerted bank runs.

1.3.2 Organisation

The exploratory System Dynamics model is presented in section 2 and its behaviour is analysed (in an exploratory sense) in section 3. The ESD is subsequently used for ESDMA in section 4. Concluding remarks and recommendations are formulated in section 5.

SD and SD diagrammatic conventions are briefly explained in appendix A. A 'hot testing & teaching case' corresponding to the base model is provided in appendix B (the sim of the hot case and base model is available at `http://forio.com/simulate/simulation/e.pruyt/dsb`). And appendix C contains the ESDMA outputs referred to in section 4.

2 An Exploratory System Dynamics Simulation Model of a Concerted Bank Crisis

An exploratory System Dynamics simulation model is presented in this section. It may be wise for readers without SD foreknowledge to get acquainted to traditional SD and SD diagrammatic conventions before reading the remainder of this paper. These readers are advised to start with appendix section A on page 22 first.

The exploratory System Dynamics model presented in this section was developed on the morning of Pieter Lakeman's call, without any information about the further course of events. It was made and simulated in order to foster understanding about the possible mechanisms and dynamics of concerted bank runs, and to test some high-level policies to prevent concerted bank runs from succeeding. The model is small, simple, high-level, exploratory, data-poor (no specific structures nor detailed data about DSB beyond some crude guestimates were added), and history-poor (previous and subsequent events were not included). The model was really used in an ex-ante exploratory way: developments were not awaited for, and the model has not been calibrated at a later moment in time to the actual course of events. The model has nevertheless value as an introduction to concerted bank runs and as an simple example of ESD and ESDMA.

The applied goal of this paper is to present and use an exploratory SD model of a concerted bank run in order to generate general insights into the potential dynamics of such financial crises, not to present a detailed 'going concern' model validated upon past conditions that represents the inner functioning of banks for all situations. Generative mechanisms for going concern banking are more complex than the generative mechanisms dominant during acute bank crises. The model presented in this paper only focuses on a bank crisis provoked by a (concerted) bank run: the model therefore does not focus on explicit stocks and flows of money through the bank –and the underlying bank's net worth– as in (MacDonald and Dowling 1993), nor on detailed operations and decisions of a commercial bank as in (MacDonald 2002).

In that sense, the model presented here is closer to crisis models like the Fortis Bank model (Pruyt 2009b) and the Northern Rock model (Rafferty 2008) than to traditional bank models. Since the model is a short-term crisis model, it is assumed that (i) there is no change in assets due to profits, (ii) *fixed and guaranteed deposits and loans* do not come at terms, (iii) there are no net shifts from liquid to fixed assets, and (iii) there are no net shifts from liquid to fixed deposits and loans.

The basic model structure of the exploratory SD model is visualised in Figure 1 by means of a Stock-Flow diagram. Data/numbers used in this section are fictitious or just guestimates, and are used for illustrative purposes only. Most of the numbers and some of the functions described in this section will be varied –and their influence explored– in the following sections.

Deposits that are emptied are –in this model and from the point of view of the bank– *liquid deposits and loans lost*. These *liquid deposits and loans lost* drain the *liquid deposits and loans*, which are assumed to amount initially to €4,500,000,000.

Liquid assets lost are equal to the *liquid deposits and loans lost* because of the double accounting system. *Liquid assets lost* decrease the stock of *liquid assets*, which initially amounted to €1,150,000,000. It is assumed here that there is a *liquid asset liquid liability target* of 20%, which means that *fixed assets*, which initially amounted to €4,600,000,000, need to be liquidated and turned into *liquid assets* if less than 20% of *liquid deposits and loans* are covered by *liquid assets*. Assuming that the *liquidation time* is only 1 day, which means that there are enough interested parties to almost instantly sell assets to, there is a *liquidation premium* of 10% on these emergency sales. In other words, only 90% of the fixed asset value is turned into liquid assets in these emergency sales, and 10% of the fixed asset value is lost as *liquidation losses*. It is supposed that DSB also administered *fixed deposits and loans* worth €1,000,000,000 which remained constant during the crisis because *fixed deposits and loans* cannot be emptied by depositors or lenders before their due date.

In a normal bank run, the amount of *liquid deposits and loans lost* equals the *liquid fraction running away* times the *liquid deposits and loans* divided by the *withdrawal time*. However, two factors amplified the running away effect in the case of DSB crisis: clients were angry because of unacceptable sales practices and the mediatised unwillingness of the bank to compensate the victims of these practices, and people understood the hindrance of a bank failure[6] after having

[6]Even without losing money (in case of depositor guarantees), depositors have to wait for months to get their money back.

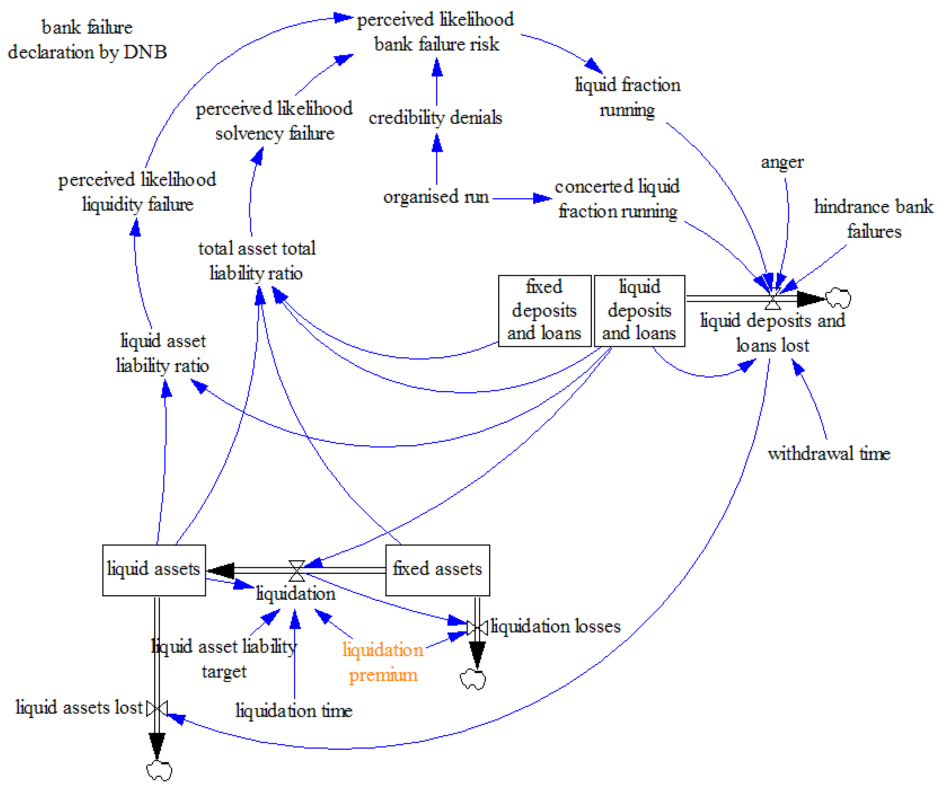


Figure 1: Stock-Flow Diagram of the basic DSB model

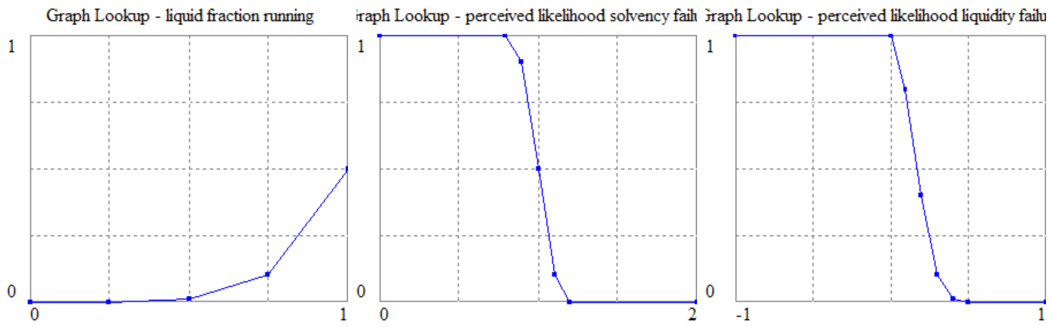
witnessed several bank failures in the months preceding the run on the DSB Bank. The previous right hand side of the equation is therefore multiply by two factors: (1+*hindrance of bank failures*) and (1+*anger*). In the base simulation, it is assumed that the *anger* and *hindrance of bank failures* amount to 0.5.

Since the DSB bank run was actually to some extent an organised bank run, an additional term is taken into account for this concerted action: *concerted liquid fraction running away* times *liquid deposits and loans* divided by *withdrawal time* of 1 day. The maximum amount of *liquid deposits and loans lost* equals the amount of *liquid deposits and loans* divided by the *withdrawal time.*

In the basic model, it is supposed that the *liquid fraction running away* amounts to 0% if the *perceived likelihood of a bank failure* is 0%, that it amounts to 0% if the *perceived likelihood of a bank failure* is 25%, that it amounts to 1% if the *perceived likelihood of a bank failure* is 50%, that it amounts to 10% if the *perceived likelihood of a bank failure* is 75%, and that it amounts to 50% if the *perceived likelihood of a bank failure* is 100% (see Figure 2(a)).

The *perceived likelihood of a bank failure* is modelled as (100% - *credibility of the denials*) times the maximum of either the *perceived likelihood of a liquidity failure* or the *perceived likelihood of a solvency failure.*

In this base version of the model, it is assumed that the *perceived likelihood of a liquidity failure* amounts to 100% if the *liquid asset liquid liability ratio* equals -1, that it amounts to 100% if the *liquid asset liquid liability ratio* equals 0, that it amounts to 80% if the *liquid asset liquid liability ratio* equals 0.1, that it amounts to 40% if the *liquid asset liquid liability ratio* equals 0.2, that it amounts to 10% if the *liquid asset liquid liability ratio* equals 0.3, that it amounts to 1% if the *liquid asset liquid liability ratio* equals 0.4, that it amounts to 0% if the *liquid asset liquid liability ratio* equals 0.5, and that it amounts to 0% if the *liquid asset liquid liability ratio* equals 1 (see



(a) *liquid fraction running away* lookup function
(b) *perceived likelihood of a liquidity failure* lookup function
(c) *perceived likelihood of a solvency failure* lookup function

Figure 2: Quickly inserted lookup functions for three critical variables (the two perceived likelihood functions are replaced by continuous parameterised ESDMA functions in the ESDMA – see Figure 11)

Figure 2(b)).

It is also assumed that the *perceived likelihood of a solvency failure* amounts to 100% if the *total asset total liability ratio* equals 0, that it amounts to 100% if the *total asset total liability ratio* equals 0.8, that it amounts to 90% if the *total asset total liability ratio* equals 0.9, that it amounts to 50% if the *total asset total liability ratio* equals 1, that it amounts to 10% if the *total asset total liability ratio* equals 1.1, that it amounts to 0% if the *total asset total liability ratio* equals 1.2, and that it amounts to 0% if the *total asset total liability ratio* equals 2 (see Figure 2(c)).

The three lookup functions described above and displayed in Figure 2 are replaced in Figure 11 by parameterised logistic functions in order to explore the influence of these functions on the model behaviour.

The *liquid asset liquid liability ratio* equals the amount of *liquid assets* over the amount of *liquid deposits and loans*. And the *total asset total liability ratio* equals the sum of the *fixed assets* and the *liquid assets* over the sum of the *liquid deposits and loans* and the *fixed deposits and loans*.

It is assumed here that the central bank issues a *bank failure declaration* (forcing a bank into bankruptcy) if the *liquid asset liquid liability ratio* falls below 0.05 or the *total asset total liability ratio* falls below 0.9 [these values are fictitious and are used for illustrative purposes only].

The immediate reaction following on Pieter Lakeman's call is introduced in the model by the *concerted liquid fraction running away* jumping to 5% on day 2 and falling down to 0% on day 4, and the *credibility of the denials* falling from 90% to 10% from day 2 on.

3 ESD: Fast and Intuitive Exploration of Uncertain Behaviours and Effectiveness of Policies

Figures 3 and 4 allow to trace the dynamics of the main variables for four different scenarios.

All variables –also the *liquid deposits and loans lost* and the *perceived likelihood of a bank failure*– remain constant if there is no anger nor perceived hindrance, if there is no loss of *credibility of denials*, or if there is no call for a concerted bank run (see the DSB0 scenario displayed in green in Figures 3 and 4).

However, with Pieter Lakeman's call, 50% *anger*, 50% *expected hindrance of a bank failure*, and a *liquidation premium* of 15%, the initial concerted run is followed by a relatively long period of liquid deposit and loan losses reducing the *liquid deposits and loans* and the *liquid assets* –which

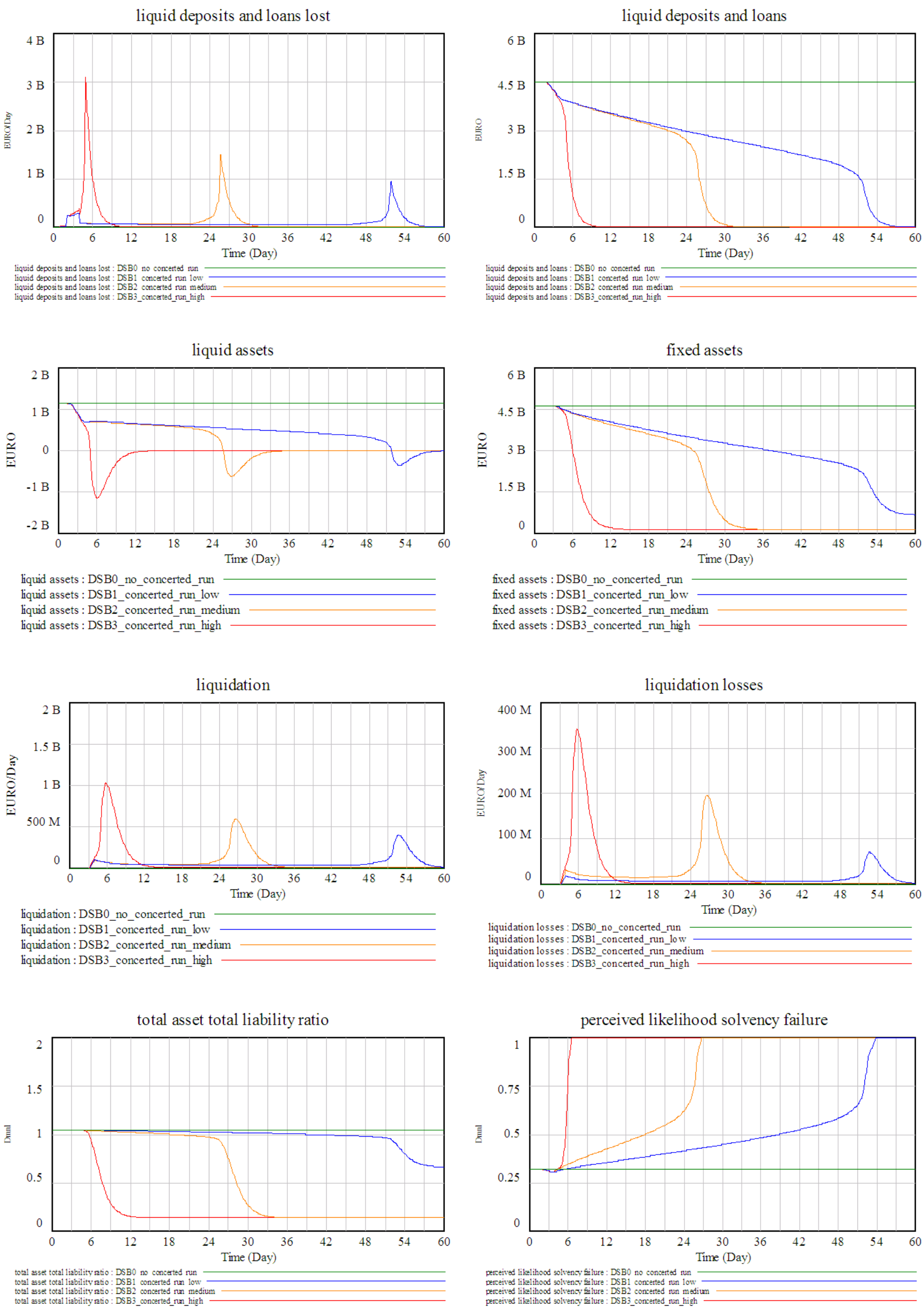


Figure 3: Behaviour of different scenarios for the 'concerted bank run' model (1/2)

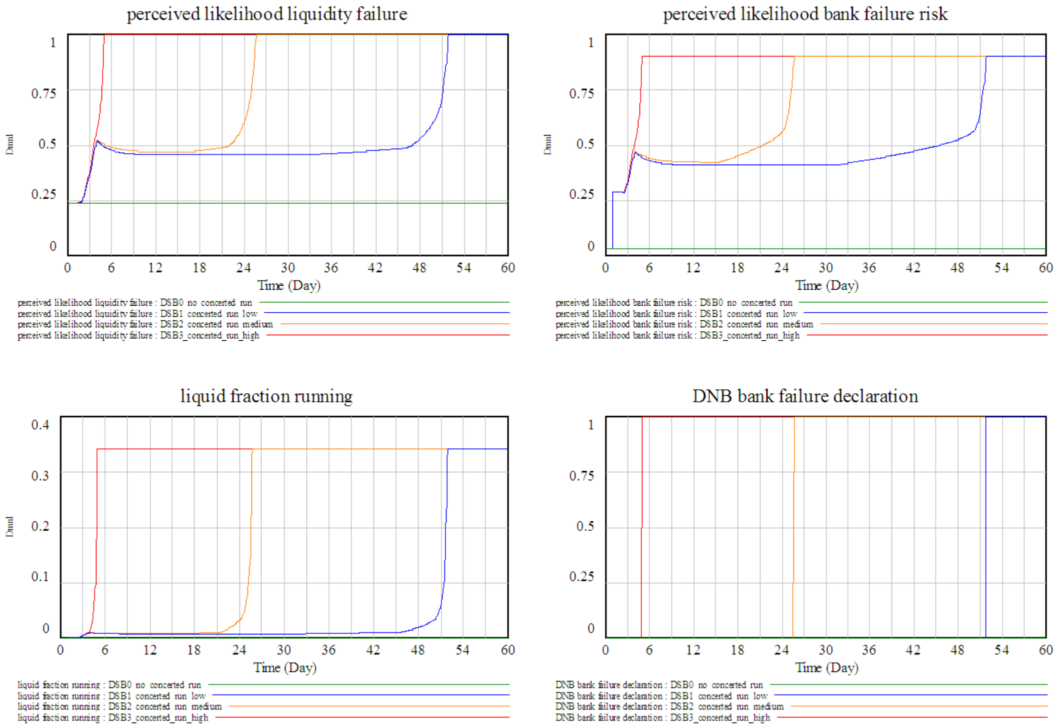


Figure 4: Behaviour of different scenarios for the 'concerted bank run' model (2/2)

are replenished by *liquidation* of *fixed assets*– until it pushes the *perceived likelihood of a bank failure* up causing a second bank run and a sudden collapse of the bank (see the DSB1 scenario displayed in blue in Figures 3 and 4). In this case, liquid deposits and loans are lost during 3 weeks before the second bank run finishes off the bank. In that case, there may still be enough time to save the bank. They could for example raise interest rates paid on (deposits and) loans in order to raise 'fresh' money to compensate the liquid deposits and loans lost.

The DSB2 scenario (displayed in orange in Figures 3 and 4) shows that the collapse occurs sooner with a *liquidation premium* of 25%. And the DSB3 scenario (displayed in red) shows that the concerted bank run is followed immediately by a full collapse of the bank in case of 100% *anger*, 100% *expected hindrance of a bank failure*, and a *liquidation premium* of 25%. In that case, the second bank run follows so fast upon the first concerted run, that there is little the bank can do to stop the bank run: there is simply not enough time to react unless preventive measures had been taken beforehand. Figure 5 shows clearly that the peaks in *liquid deposits and loans lost* are actually caused by the depletion of the stock of *liquid deposits and loans*.

Although the bank –at least for this particular ESD model formulation and for the parameter values used– seems to collapse sooner or later after an initial perturbation of sufficient amplitude, the delay with which the second run follows upon the concerted run makes a big difference for those involved: in scenarios DSB1 and DSB2 there seems to be some time for strategies/policies and anticipative crisis management, but not in scenario SDB3, in which the second run follows immediately upon the first run, in which case there may only be time for preventive mechanisms put in place in the past, emergency measures (such as increasing the *withdrawal time* or limiting the amounts that can be withdrawn per account per day) and reactive crisis management, or an 'emergency measure' that places the bank under legal restraint.

However, the fact that the modelled bank seems to collapse sooner or later may partly be due to the fact that this version of the model is a crisis model without any protective checks

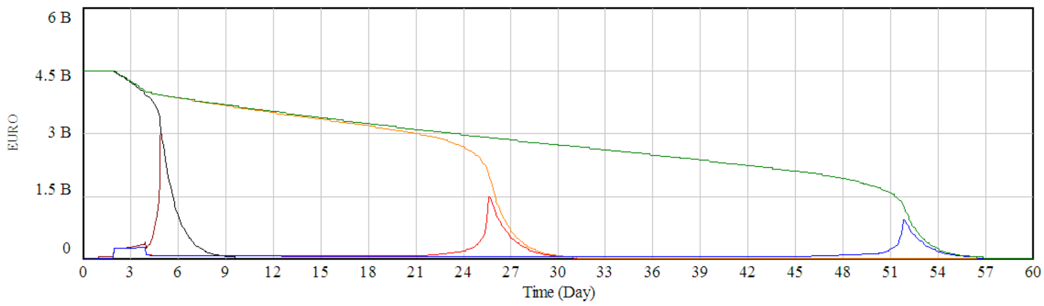


Figure 5: *liquid deposits and loans* and *liquid deposits and loans lost* following the concerted bank runs

and balances and/or policies for dealing with such crises. The *causal loop diagram* in Figure 3 shows indeed that the positive liquidity and solvency loops make that the likelihood of a bank failure keeps on increasing –unless actively stopped– until the bank collapses. This could have been expected given the fact that revenues and profits are not generated or added to the asset base here: in this version there is only a reinforcing drain without replenishment (see below for replenishment options).

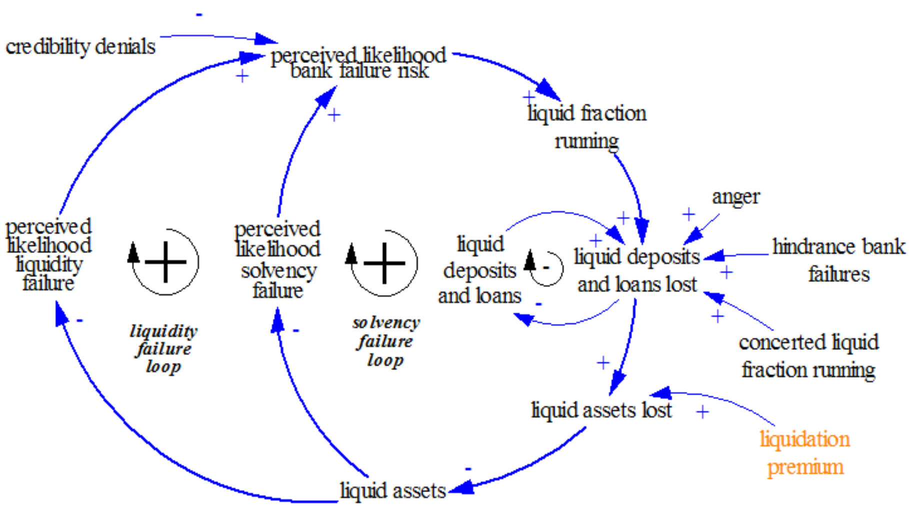


Figure 6: Main feedback loops responsible for the second bank run induced by the concerted bank run

Manual sensitivity analyses, automated Monte-Carlo simulations, scenario analyses, what-if analyses, and policy analyses are traditionally performed in SD modelling to check whether the model is sensitive to small parameter changes, to assess and visualise the confidence bounds given probabilistic parameter inputs, to assess the modes of behaviour of different sets of conditions, and to explore the change in behaviour given the occurrence of events, changes in conditions or implementation of policies.

These traditional SD analyses may be slightly less useful –at least in their traditional form, for their traditional purposes, and in their traditional interpretation– for exploratory SD.

Take for example a traditional Monte-Carlo analysis: based on the the aggregated outcomes of 1000 runs sampled using Monte-Carlo sampling from normal distributions for the variables anger and expected hindrance possible bank failure, both N(0.5,0.1) displayed in Figure 7, some may conclude that the bank will collapse sometime between 32 and 75 days after the call for the concerted bank run – and most likely between 48 and 57 days after the call. But from an exploratory point of view, that cannot possibly be concluded from this exploratory model and this rather narrow and intuitive analysis.

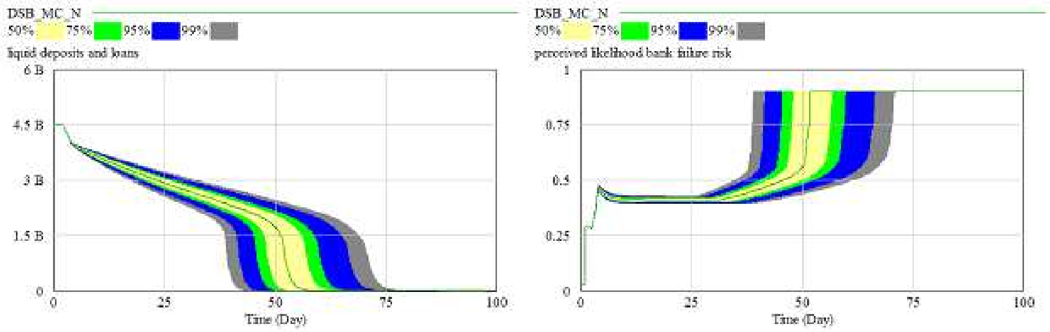


Figure 7: 1000 Monte-Carlo runs with anger $\sim N(0.5, 0.1)$ and hindrance bank failures $\sim N(0.5, 0.1)$

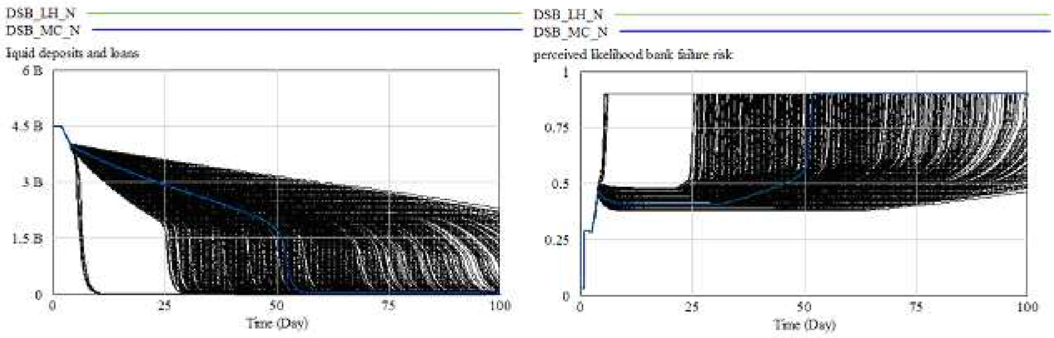


Figure 8: 1000 individual traces of Latin Hypercube sampled runs with anger $\sim U(0, 1)$ and expected hindrance of a possible bank failure $\sim U(0, 1)$

The bounds in Figure 7 cannot possibly –from an exploratory point of view– be interpreted as likelihoods: the exploration is much too narrow –in terms of distributions, sampling technique (Monte-Carlo 1000), and uncertainties explored (only parametric uncertainty of just two variables)– for exploratory purposes. By just changing the sampling technique (to Latin Hypercube), the distributions sampled from (to Uniform distributions U(0,1)), and displaying individual traces instead of confidence intervals, a different picture already emerges (see Figure 8).

It looks as though there are two slightly different types of behaviour in Figure 8 –which was not the case in Figure 7– and that there is a bifurcation between runs in which the bank immediately collapses and runs in which the bank only collapses after a 'bleeding' time.

Neither can exploratory SD models be used for meaningfully answering traditional *what-if* questions: exploratory SD outputs cannot be interpreted in a (strongly or weakly) predictive sense which means that outputs of what-if analyses can at most be considered to be '*plausible outcomes if this or that happens in this particular model with these particular values*'. Exploratory what-if analyses and exploratory scenario analyses are nevertheless very useful from an exploratory point of view for exploring plausible futures as already illustrated above (DSB1, DSB2 and DSB3 scenarios discussed and displayed above).

Traditionally, the effectiveness of policies/strategies for dealing with undesirable behaviours (in this case all scenarios but the green one) is then tested. Such policy analyses certainly make sense from an exploratory point of view, but the conclusions cannot be more than indicative, most certainly not predictive, prescriptive and/or conclusive.

We expect relatively simple, adaptive, conditional closed-loop policies/strategies to be most effective over the entire ensemble of futures, and therefore to be more robust, as well as understandable and intuitively most appealing.

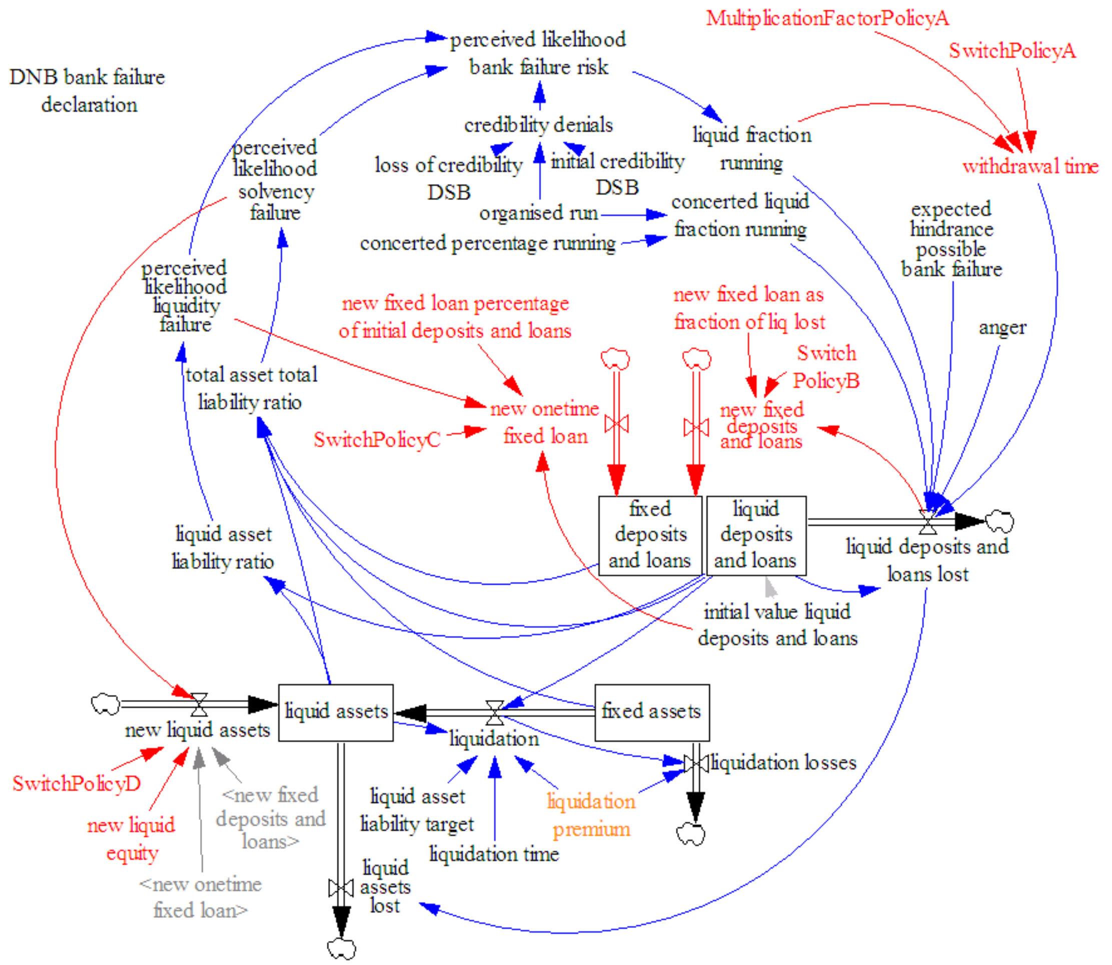


Figure 9: SFD of the 'concerted bank run' model with four policies (displayed in red)

Following simple policies are tested here –mainly for illustrative purposes– for the exploratory DSB Bank model (the necessary structures are included in Figure 3 in red):

- ***Policy A*** is a simple closed loop policy for slowing the –or decreasing the amount of– *liquid deposits and loans lost* by influencing the *withdrawal time*[7]. This policy seems to have been applied to some extent in the real DSB Bank crisis too: its e-banking site became terribly slow during the crisis, 'officially' because the site was attacked by hackers. Although not included here, this policy may also create an unintended positive 'panick' feedback effect.
- ***Policy B*** ensures that a fraction –50% in this case– of the *liquid deposits and loans lost* are replaced at each and any time by *fixed deposits and loans.*

[7] *withdrawal time* = 1 + *liquid fraction running* * *MultiplicationFactorPolicyA*; with *MultiplicationFactorPolicyA* = 20.

- ***Policy C*** ensures that a *new onetime fixed loan* equal to the *initial value liquid deposits and loans* times the *new fixed loan percentage of initial deposits and loans* (here equal to 20%) is contracted if (and only if) the *perceived likelihood liquidity failure* rises above 50%.
- ***Policy D*** ensures that *new liquid equity* amounting to €250000000 is added if (and only if) the *perceived likelihood of a solvency failure* rises above 50%.

Figure 10 visualises the impacts of these four policies/strategies on the *liquid deposits and loans* and the *perceived likelihood bank failure risk* for scenarios DSB1, DSB2, and DSB3. There it can be seen that:

- Policy A just slows the fall, but does not prevent it from happening;
- Policy B stops the fall by gradually substituting *liquid deposits and loans* by more expensive *fixed deposits and loans* in case of DSB1 and DSB2, but not in the longer run in case of DSB3;
- Policy C allows to deal with the threat but may require multiple fixed loans while gradually losing liquid deposits and loans;
- Policy D allows to stabilise the bank in time by solving the solvency problem, except in scenario DSB3 where the solvency crisis is solved after the liquidity has resulted in a collapse (the black and green line coincide). However, by combining policies A and D, the acute liquidity problem is dealt with by policy A and the solvency problem by policy D.

It should be noted that the cost of these policies is not equal and that the policies have not been explored systematically here.

Although scenario analyses, risk analyses, and policy analyses and their the exploratory interpretation make more sense from an exploratory point of view than the corresponding traditional analyses and interpretations, it could still be argued that they are not sufficiently broad and systematic to firmly base policy making under deep uncertainty on. Indeed, just exploring the (combined) effect of three parametric uncertainties by means of four scenarios can hardly be called systematic. A more systematic exploration of uncertainties is the topic of the following section.

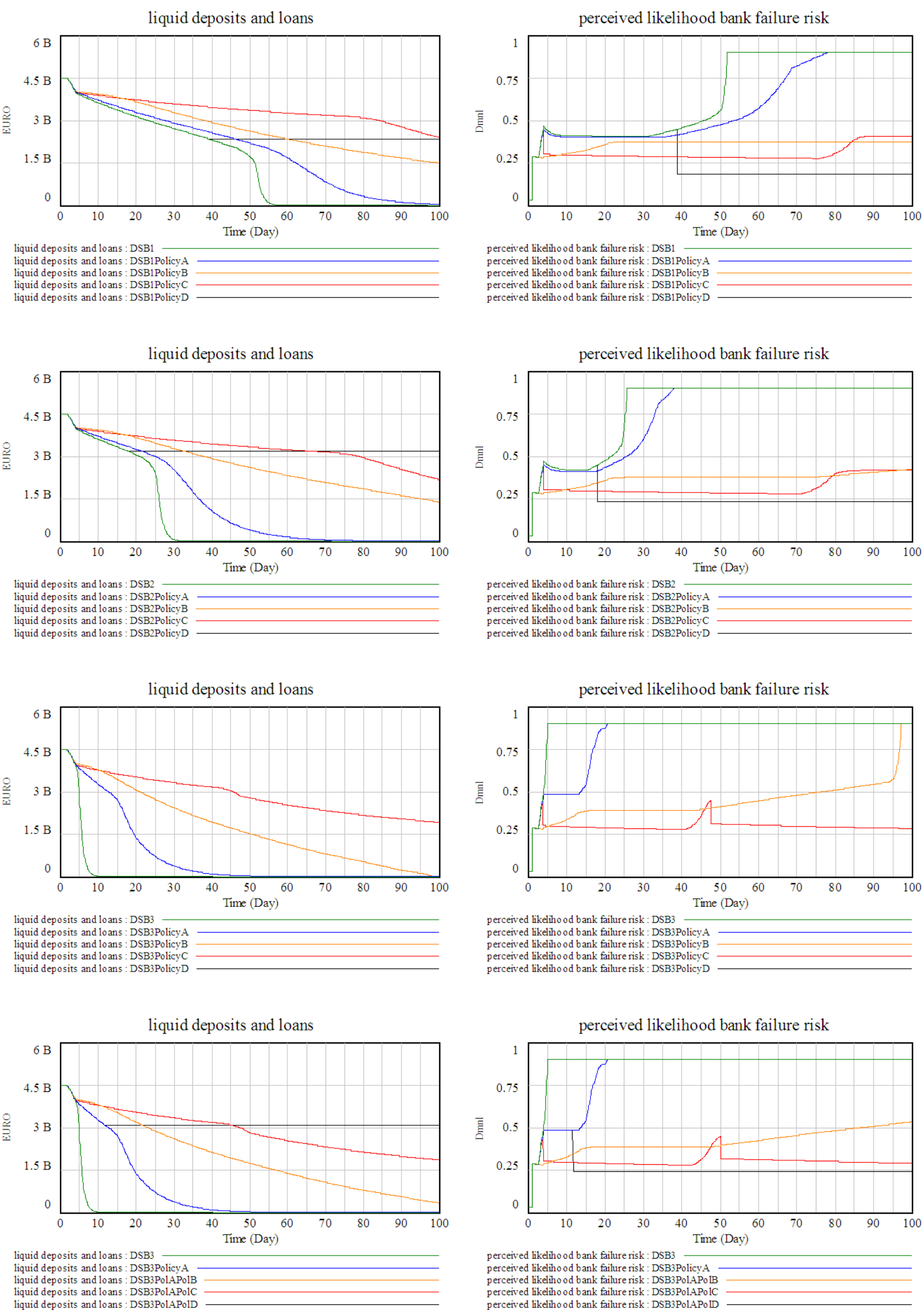


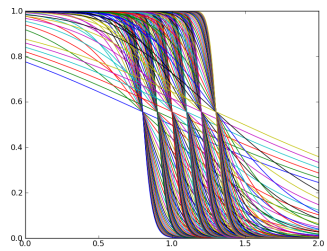
Figure 10: Four different policies and one combined policy applied for three different scenarios

4 ESDMA: Systematic Exploration of Uncertain Behaviours and Policy Robustness

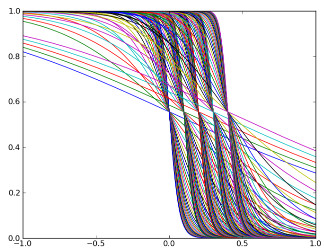
The ESDMA discussed here is kept as simple as possible: only one ESD model is used to explore the influence of 'simple' uncertainties (parametric uncertainties and uncertainties related to the formulation of the three lookup functions) in terms of the resulting dynamic behaviours and bifurcations, and test the effectiveness and robustness of some policy options given these 'simple' uncertainties. The input for this analysis consists of thousands of full factorial samples from broader parameter ranges (e.g. 0–1 instead of 0.15–0.25) and from parameterised functions, without fundamentally changing the model structure (see (Pruyt and Hamarat 2010) for an example of ESDMA with slightly different models).

The two logistic lookup functions displayed in Figures 2(b) and 2(c) are replaced –in order to explore the influence of uncertain (lookup) functions on the model behaviour– by the parameterised (logistic) functions displayed in Figure 11: parameters for the inflection point, the skewness, and the decay rate of these functions are varied.

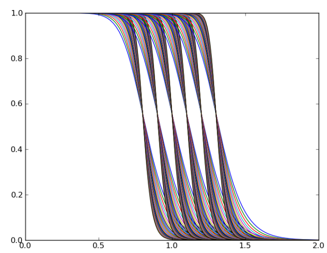
Figure C.1 shows 25 graphs of the dynamics of the *liquid deposits and loans* for different inclination points of the *perceived likelihood of solvency failure* and *perceived likelihood of liquidity failure* functions, with 900 (full factorial) samples of the skewness of the latter functions per graph.



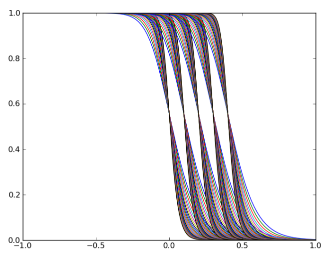
(a) *perceived likelihood of a solvency failure* function used in Figures C1 and C2 in app C



(b) *perceived likelihood of a liquidity failure* function used in Figures C1 and C2 in app C



(c) *perceived likelihood of a solvency failure* function underlying Figures C3, C4, C5 in app C



(d) *perceived likelihood of a liquidity failure* function underlying Figures C3, C4, C5 in app C

Figure 11: Fully parameterised continuous ESDMA functions (replacing two of the lookup functions in Figure 2)

Figure C.2 zooms in on the apparent 'bifurcation' of the dynamics of the *liquid deposits and loans* as displayed in the first column of Figure C.1, between the graphs in the second and third rows. This 'filmstrip' shows the behaviour for various degrees of skewness of the *perceived likelihood of solvency failure* and *perceived likelihood of liquidity failure* functions for different x-values of the inflection point of the *perceived likelihood of liquidity failure* function ranging from 0.185 to

0.200 and for a fixed value of the inclination point of the *perceived likelihood of solvency failure* function of 0.8. The film strips show that more and more clusters of trajectories start to drop as the x-value of the inflection point of the *perceived likelihood of liquidity failure* increases.

Hence, Figures C.1 and C.2 show that the different shapes and shifts of the inclination points of these two uncertain functions matter a lot for the resulting dynamics of the bank run and the time available for intervention. However, the importance of the outcomes of the uncertainty analyses for these two functions should not be overemphasized: within the bigger uncertainty picture, these functions are just two of the uncertainties and more of them should be explored.

Before exploring the combined effect of even more uncertainties, it makes sense to check whether clear structures can be discerned in the trajectory data generated while changing several uncertainties considered. The dimensionless resemblance plot[8] displayed in Figure C.3 shows that clearly distinctive clusters of similar trajectories can be discerned (in a sample of 5000 out of 40000 trajectories)[9].

Now that we know that there is enough structure in the data to pursue further detailed analyses of the behaviours, it makes sense to visualise the outcomes of the 40000 trajectories generated by combining different values of the uncertainties considered, more precisely:
for liqskew = 0.0 - 0.1 - 0.2 - 0.3 - 0.4
for solskew = 0.9 - 1.0 - 1.1 - 1.2 - 1.3 - 1.4
for liqgrow = 10 - 15 - 20 - 25
for solgrow = 10 - 15 - 20 - 25
for anger = 0.2 - 0.4 - 0.6 - 0.8 - 1.0
for exp. hindrance = 0.2 - 0.4 - 0.6 - 0.8 - 1.0
for loss cred. = 0.2 - 0.4 - 0.6 - 0.8.

Figure C.4 contains the trajectories of the *liquid deposits and loans* of 48000 runs split out in 1600 runs in each of the 30 graphs according to different combinations of inflection points of the *perceived likelihood of liquidity failure* and *perceived likelihood of solvency failure* functions.

Looking at the overall picture, four patterns can be clearly distinguished for high parameter values of the solvency and liquidity inclination points. Very low values for both parameters only generated a gradual decline. In between there is a clear transition zone where more and more clusters of trajectories break down.

Information about the timing of the simulated bank failures is displayed in Figure 12 –which should not be interpreted in a probabilistic sense. This figure displays shows 22755 bank failures within the first three months out of a total of 40000 runs – the remaining 17245 trajectories do not collapse (entirely) within this time horizon. However, these graphs and numbers cannot be interpreted in a probabilistic sense because of the exploratory nature of the model, the extreme uncertainty about the real underlying probabilities, the full factorial design together with the uniform density functions used, etc. Based on the outcomes of the bank failure declaration, they show that this model together with these uncertainties generate four dominant types of runs: the modelled bank either collapses immediately, or it collapses in the short term (after 10 to 20 days in this model), or it collapses in the medium term (after two to four months in this model), or it does not collapse within the time horizon considered.

These detailed analyses are –given the fact that probabilistic interpretations for this exploratory model are not possible– only really useful as a starting point for an exploratory policy analysis: both for designing (adaptive) policies and testing their effectiveness and robustness, and for comparing them with the outcomes of the no-intervention base case.

The same simple policies that were tested in the ESD policy analysis in section 3 are tested here in this ESDMA policy analysis. In the full factorial design of the ESDMA policy analysis, the

[8] We are very grateful to Jan Kwakkel for generating this plot and his critical reflections on our work on ESDMA.

[9] The scripts and techniques to determine automatically what the clusters represent are currently under development. As for now, we can only guess what the shape of this particular resemblance plot really means.

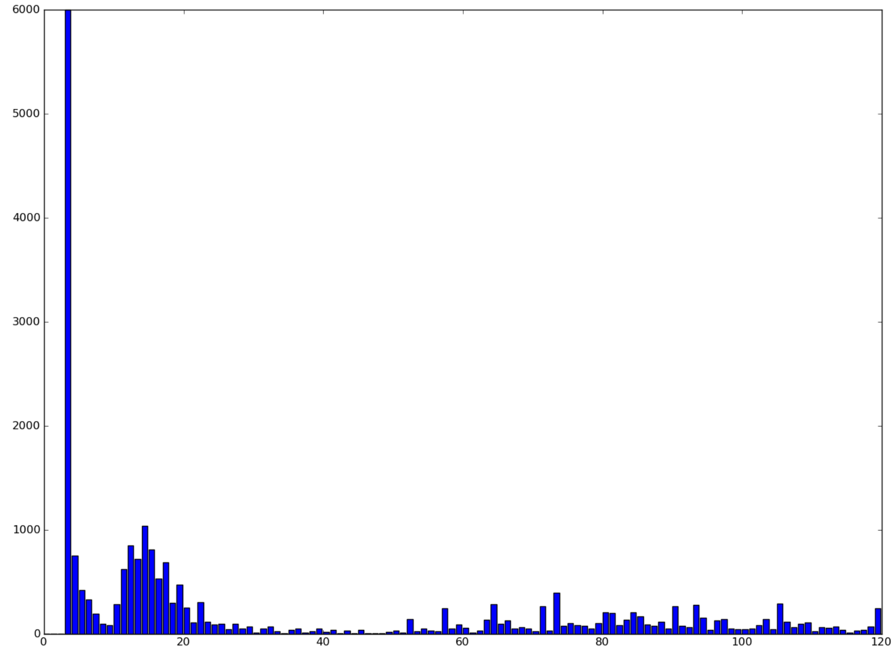


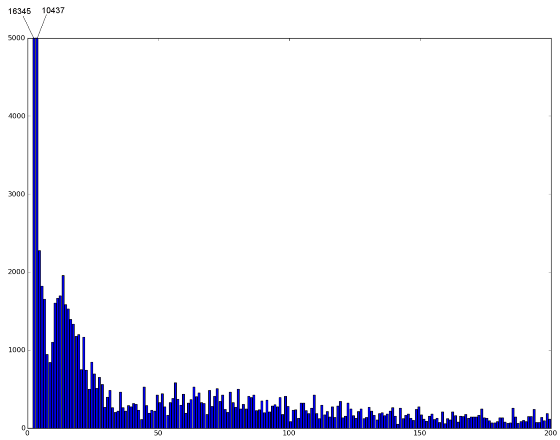
Figure 12: Bar graph of 22755 bank failures out of 40000 runs – the remaining 17245 trajectories do not collapse (entirely) within the time horizon simulated here

liquidity premium is varied (0.10 ; 0.15 ; 0.20, 0.25 ; 0.30) on top of previous variations. Adding the variations of the *liquidity premium* makes the clusters of trajectories slightly less distinctive. In stead of displaying the trajectories, we immediately display the bank failures as in Figure 12. Figure 13 gives a visual impression of the effectiveness of these policies, in other words, whether they help to avoid or delay a bank failure. Starting with the base case, a considerable number of runs collapses immediately, or in the short term, or spread out over the medium term, or not at all (103508 out of 200000 runs). Policy A delays the immediate collapses from the very short term to the short term and only leads to a minor reduction (about 1%) of the number of collapses in the time horizon considered. Policy B leads to slightly more immediate collapses, but almost eliminates short term and medium term collapses by solving the liquidity problem. Policy C outperforms policy B in the very short term and over the entire horizon, but not in the short and medium term. And policy D reduces –compared to the base case– the number of collapses over the whole line, but not as much as policies B and C. Policy D helps to solve solvency problems, but is less appropriate for solving acute liquidity problems. That problem could be partly solved by combining policy D with policy A (see Figure 13(f)). This combined policy eliminates immediate collapses, and strongly reduces all other types of collapses.

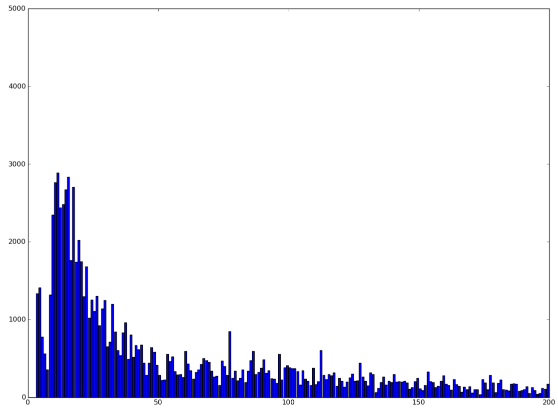
For real cases it is interesting at this point to compare the efficiency, effectiveness, and robustness of these policies and to to experiment with policies of different strength as well as with different combinations of policies.

It would also be really interesting to explore the scenario spaces for which policies are *not* effective yet using for example the PRIM algorithm (see (Bryant and Lempert 2009)). This, however, is work in progress[10].

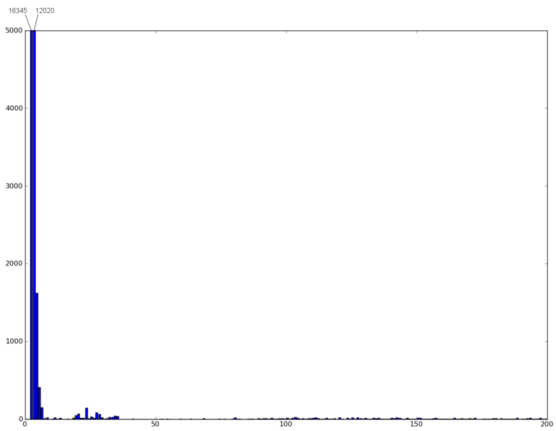
[10] It is extremely likely that we will have made all currently known changes and improvements, and will have implemented/applied promising algorithms and new coding to perform more advanced analyses and obtain better visualisations.



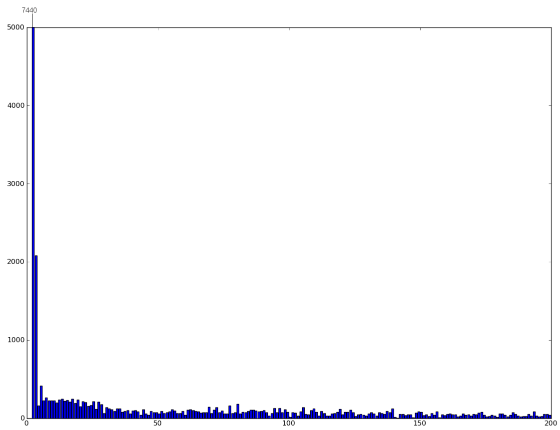
(a) No policy – 103508 runs out of 200000 do not collapse within the time horizon – first bar = 16345; second bar = 10437



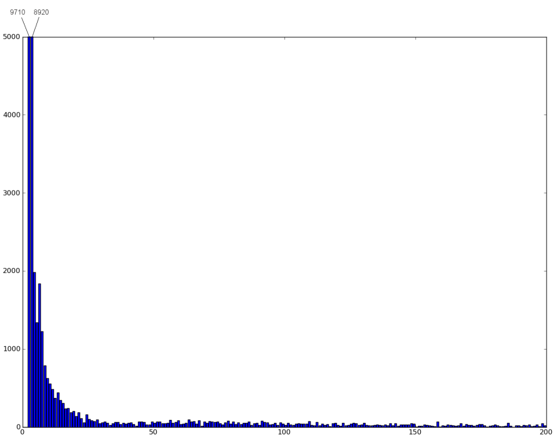
(b) Policy A – 105104 runs out of 200000 do not collapse within the time horizon



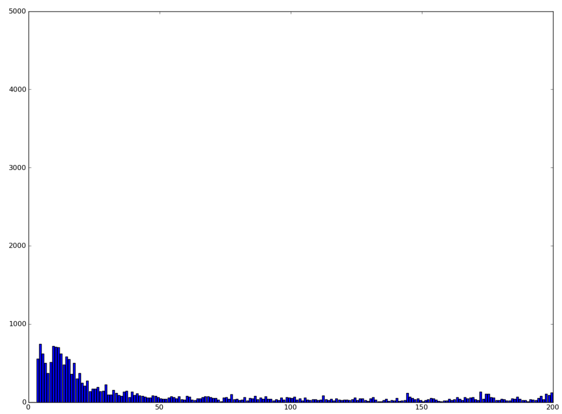
(c) Policy B – 167968 runs out of 200000 do not collapse within the time horizon – first bar = 16345; second bar = 12020



(d) Policy C – 173800 runs out of 200000 do not collapse within the time horizon – first bar = 7440



(e) Policy D – 163738 runs out of 200000 do not collapse within the time horizon – first bar = 9710; second bar = 8920



(f) Policy A + D – 180564 runs out of 200000 do not collapse within the time horizon

Figure 13: No Policy, Policy A, Policy B, Policy C, Policy D, Policies AxD – all applied to an ensemble of 200000 scenarios, over 200 days, and with a maximum Y-axis value of 5000 [runs]

5 Conclusions

Many banks collapsed in 2008-2009. At least one of them collapsed after a public call for a bank run. This paper presents an Exploratory System Dynamics (ESD) model of such a concerted bank run. The model is a rather traditional 'dynamic bank run model' with an exogenous call possibly triggering a second run. The model was developed the same morning of the call in order to explore possible behaviours and consequences. Hence, the model is really modelled as a short term crisis model. It is exploratory in terms of its goals, size, scope, and level of aggregation/simplification. Keeping in mind that the model used is a simplistic and rather ideal model, it may be concluded from the ESD simulations that:

- The public call for a run may seriously endanger the stability of a bank if sufficient depositors follow the call.
- A concerted bank run may –depending on the conditions– cause an immediate bank run, or a first run followed by a 'bleeding time' and a second run in the very short, medium or long term (or never at all).
- An isolated policy to slow the loss of liquid deposits and loans does little to prevent a second run from happening. A policy to make up for (a big) part of the liquid deposits and loans losses by gradually obtaining fixed deposits and loans (for example by raising the interest rate on those products) may work, but not in case of a high liquidation premium. A policy in which large fixed loans are sought for dealing with the liquidity problem may work, but may nevertheless lead to a gradual loss of liquid deposits and loans. And an equity policy may help to deal with the solvency problem, but does not seem to be enough for dealing with the liquidity problem. However, that may be solved by combining the latter policy with policies to deal with acute liquidity problems.

Later, this simple ESD model was used to test and (further) develop ESDMA which allows for a more systematic and broader exploration of uncertainties and policy robustness. From the ESDMA, it can be concluded that:

- It seems to be necessary in case of a concerted bank run *(i)* to be able to buy time by delaying the follow-up run such such that any acute solvency problem can be dealt with, and/or *(ii)* to put the necessary mechanisms in place that allow to deal almost instantly with acute liquidity problems.
- The ESDMA confirms the applied conclusions reached with the ESD. Different values for the policy parameters may still be explored, as well as the cost efficiency of these policies.

The ESDMA described in this paper is also exploratory in the sense that it was our first EMA on an ESD model using the Python language/package. Hence, all scripts and coding were developed and/or used for the first time. This is also the main reason for the lack –in the current version of the paper– of an systematic ex-ante design of the uncertainty explorations: one of the major lessons learned is that a decent ex-ante ESDMA design is needed to make the exploration process more efficient.

Still it can be concluded from a methodological point of view that:

- ESD is useful for very quickly and somewhat intuitively exploring uncertain dynamically complex issues. It may for example be used for generating –very different– *plausible* dynamic behaviours that may support the reflection process – as 'tools for thinking'. It may also be used to reason about policies. But in isolation, it may also be criticised for being too intuitive, narrow and unsystematic to base real world policies on.
- ESDMA is useful for systematically exploring *possible* behaviours of uncertain dynamically complex issues as well as the efficiency and effectiveness/robustness of potential solutions

under deep uncertainty. It may for example be used to systematically scan and analyse all possible behaviours that can be generated by taking parametric and structural uncertainties seriously into account.

In the near future, we will work on cases of increasing complexity in order to gradually advance our work on ESDMA. In this paper, we already included uncertainty ranges and different formulations/functions. Simple analysis and visualisation techniques were good enough here because the behaviours generated with the DSB model were clearly distinctive. In the next stage, we will simultaneously explore different model formulations (see (Pruyt and Hamarat 2010)). Future work will include considering different world views with very different models and preferences. Each of these steps will lead –at first sight and without good analyses and visualisation techniques– to more and more chaotic behaviours. We will therefore also explore better ways to deal with problems of combinatorial complexity, and develop better and more user-friendly methods, techniques, and tools, starting from existing analysis methods, data mining techniques, mathematical and control theory techniques, formal modelling methods, and multi-dimensional visualisation techniques.

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A System Dynamics and Diagrammatic Conventions

SD models consist of specific structural elements causally linked into feedback loops. These models only contain *direct causal* relations (e.g. the blue links in Figure 14). For SD to be of any use, it is required that possible causal links can be perceived or hypothesised. Causal influences are either positive or negative. A *positive causal influence* –indicated by a blue arrow with a '+' sign in Figure 14– means that if the influencing variable increases (decreases), all things being equal, the influenced variable increases (decreases) too above (under) what would have been the case otherwise, or $A \xrightarrow[+]{} B \Rightarrow \frac{\partial B}{\partial A} > 0$. In other words, 'a positive arrow from A to B means that A adds to B, or, a change in A causes a change in B in the same direction' (Richardson 1997, p249). A *negative causal influence* –indicated by a blue arrow with a '-' sign in Figure 14– means that if the influencing variable increases (decreases), all things being equal, the influenced variable decreases (increases) under (above) what would have been the case otherwise, or $A \xrightarrow[-]{} B \Rightarrow \frac{\partial B}{\partial A} < 0$. In other words, '[f]or a negative link from A to B one says A subtracts from B, or a change in A causes a change in B in the opposite direction' (ibidem).

A *feedback loop* consists of two or more causal influences between elements that are connected in such a way that if one follows the causality starting at any element in the loop, one eventually returns to the first element. In other words, the variable feeds back –after some time– to itself, which makes that its behaviour is (partly) shaped by its own past behaviour. Feedback loops are either positive or negative. A feedback loop is called positive or reinforcing if an initial increase in a variable A leads after some time to an additional increase in A and so on, and that an initial decrease in A leads to an additional decrease in A and so on. Positive feedback loops in isolation generate exponential growth or decay. A feedback loop is called negative or balancing if an initial increase in variable A leads after some time to a decrease in A, and that an initial decrease in A leads to an increase in A. Negative feedback loops in isolation generate balancing or goal-seeking behaviour and can be used for automatic control/balancing.

Feedback loops give rise to nonlinear behaviour, even if all constitutive causal relationships are linear. Feedback loops almost never exist in isolation: several feedback loops are often strongly connected, and their respective strengths change over time. The feedback concept is a fundamentally important characteristic of SD.

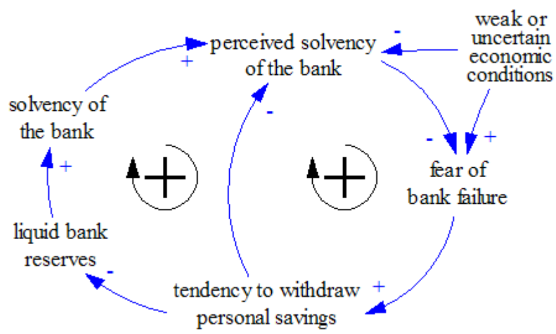

Figure 14: Causal loop diagram of a traditional bank run, based on (Richardson, 1991; MacDonald, 2002)

Causal Loop Diagrams (CLD) are often used by System Dynamicists to map (systems of) feedback loops and strongly simplified and aggregated CLDs are often used to ease the communication of the main feedback effects. Following symbols are mostly used in CLDs: $\xrightarrow[+]{}$ represents a positive causal influence; $\xrightarrow[-]{}$ represents a negative causal influence; $\xrightarrow[+]{/\!/}$ and $\xrightarrow[-]{/\!/}$ represent a positive and a negative causal influence with a delay; $\ominus$ and $\ominus$ represent negative feedback loops; and $\oplus$ and $\oplus$ represent positive feedback loops.

Figure 14 displays for example a CLD (based on (Richardson 1991) and (MacDonald 2002, p67-77)) of a traditional bank run. It reads as follows: The weaker or more uncertain the economic conditions are, the higher *the fear of bank failure* will be, and the higher the *tendency to withdraw personal savings*. A higher *tendency to withdraw personal savings* leads directly to a *lower perceived solvency of the bank* but also indirectly over lower *liquid bank reserves* and a lower *solvency of the bank*. This lower *perceived solvency of the bank* will in turn increase the *fear of bank failure* above what would have been the case, and so on.

SD models also contain *stock-flow structures*. Figure 1 shows a Stock-Flow Diagram (SFD), which graphically represents a SD simulation model, and more specifically, its stock variables (□), flow variables (⧖), auxiliary variables (◯ or no symbol), and constants (◇ or no symbol) and other direct causal influences between variables (the blue arrows). A stock variable –also called a level or a state variable– could be seen metaphorically as a 'bath tube' or 'reservoir'. During a simulation, stock variables can only be changed by flow variables (also known as rates). Every feedback loop contains at least one stock variable or memory (in order to avoid simulation problems caused by simultaneous equations).

Positive inflows increase the contents of stock variables, and positive outflows decrease their contents: ingoing flows are, metaphorically speaking, taps or valves, and outgoing flows drains. Flow variables regulate the states of stock variables. Hence, flow variables are the variables that need to be targeted by strategies to improve the problematic condition/state of the more inert stock variables.

Mathematically speaking, the stock variable is the integral of the difference between the incoming flows and the outgoing flows over the time interval considered, plus the amount in the stock at the beginning of the period. SD models are thus –if seen from a stock perspective– systems of integral equations, or –if seen from a flow perspective– systems of differential equations.

Time *delays* are also important elements of SD models. They are included in causal loop diagrams by means of slashed arrows (↛), and in stock/flow diagrams by different delay-type functions and slashed arrows (↛). *Nonlinear functions* may also be important in SD models. They are often included in computer models by means of (non-linear) table functions –also called lookup functions or graph functions.

The simulation over time of simulation models of these structural elements gives what system dynamicists are really interested in: the overall modes of behaviour. System Dynamics is not to be used for exact point prediction or path prediction (Meadows and Robinson 1985, p34).

One of the basic assumptions of SD is that the structure of a system (and model) drives its behaviour, and hence, that structural policies are needed to effectively and robustly change (possible) undesirable behaviours. System dynamicists are therefore biased in a sense that they look for structural solutions by trying to change links, feedback loops, underlying structures, etc.

B Another 'Hot Teaching/Testing' Case: The Concerted Run on the DSB Bank

The case description below was given in November 2009 to about 25 first-year MSc students and in January 2010 to about 70 second year BSc students during their time-constrained 'Introduction to System Dynamics' exam at Delft University of Technology. Although this case is smaller than most hot teaching/testing cases (see (Pruyt 2009a), (Pruyt 2010b) and (Pruyt 2010a)), students found it rather demanding because of the lack of a step-wise approach and somewhat difficult formulations.

B.1 Case Description

Over the last year, newspapers have been reporting about many bankruptcies of banks and financial institutions. The latest bankruptcy of a Dutch bank, the Dirk Scheringa Bank or DSB, is a very special case, because the bankruptcy was actually caused by a concerted bank run by angry clients following the call by Pieter Lakeman to empty their deposits.

Since you already modelled the fall of the Fortis Bank, you are asked by the Dutch central bank '*De Nederlandse Bank*' to model the fall of the DSB. Keep in mind that a crisis model is not the same as a complete bank model for going concern.

Deposits being emptied are –from the point of view of a bank– *liquid deposits and loans lost*. These *liquid deposits and loans lost* drained the *liquid deposits and loans*, which initially amounted to €4,500,000,000.

Liquid assets lost are equal to the *liquid deposits and loans lost* because of the double accounting system. *Liquid assets lost* decrease the amount of *liquid assets*, which initially amounted to €1,150,000,000. Suppose that there is a *liquid asset liquid liability target* of 20%, which means that *fixed assets*, which initially amounted to €4,600,000,000), need to be liquidated and turned into *liquid assets* if less than 20% of *liquid deposits and loans* are covered by *liquid assets*. Suppose that the *liquidation time* is only 1 day, which means that there are enough interested parties to almost instantly sell assets to. However, given this haste, there is a *liquidation premium* of 10% on these emergency sales. In other words, only 90% of the fixed asset value is turned into liquid assets in these emergency sales, and 10% of the fixed asset value is lost as *liquidation losses*. Keep in mind when you model the *liquidation* flow that the model you make is a crisis model and not a complete banking model: there should at most be a net flow from *fixed assets* to *liquid assets*, but not the other way around. Apart from the *liquid deposits and loans*, DSB also had *fixed deposits and loans* worth €1,000,000,000 which remained constant during the crisis because *fixed deposits and loans* cannot be emptied by depositors or lenders before their due date.

In a normal bank run, the amount of *liquid deposits and loans lost* equals the *liquid fraction running away away* times the *liquid deposits and loans* divided by the *withdrawal time*. However, two factors amplified the running away effect in the case of DSB crisis: clients were angry because of unacceptable sales practices and the mediatised unwillingness of the bank to compensate the victims of these practices, and people understood the hindrance of a bank failure[11] after having witnessed bankruptcies of several banks over the past few months. Multiply the previous right hand side of the equation therefore with following two factors: (1+*hindrance of bank failures*) and (1+*anger*). Suppose that the *hindrance of bank failures* amounts to 0.5.

Since the DSB bank run was actually to some extent an organised bank run, you have to add an additional term to take this concerted action into account, for example: *concerted liquid fraction running away* times *liquid deposits and loans* divided by *withdrawal time* of 1 day. And do not forget that the maximum amount of *liquid deposits and loans lost* equals the amount of *liquid deposits and loans* divided by the *withdrawal time*.

Suppose that the *liquid fraction running away* amounts to 0% if the *perceived likelihood of a bank failure* is 0%, that it amounts to 0% if the *perceived likelihood of a bank failure* is 25%, that it amounts to 1% if the *perceived likelihood of a bank failure* is 50%, that it amounts to 10% if the *perceived likelihood of a bank failure* is 75%, and that it amounts to 50% if the *perceived likelihood of a bank failure* is 100%.

The *perceived likelihood of a bank failure* may be modelled as (100% - *credibility of the denials*) times the maximum of either the *perceived likelihood of a liquidity failure* or the *perceived likelihood of a solvency failure*.

Suppose that the *perceived likelihood of a liquidity failure* amounts to 100% if the *liquid asset liquid liability ratio* equals -1, that it amounts to 100% if the *liquid asset liquid liability ratio* equals 0, that it amounts to 80% if the *liquid asset liquid liability ratio* equals 0.1, that it amounts to 40% if the *liquid asset liquid liability ratio* equals 0.2, that it amounts to 10% if the *liquid asset liquid liability ratio* equals 0.3, that it amounts to 1% if the *liquid asset liquid liability ratio* equals

[11] Even without losing money (in case of depositor guarantees), depositors have to wait for months to get their money back.

0.4, that it amounts to 0% if the *liquid asset liquid liability ratio* equals 0.5, and that it amounts to 0% if the *liquid asset liquid liability ratio* equals 1.

Suppose that the *perceived likelihood of a solvency failure* amounts to 100% if the *total asset total liability ratio* equals 0, that it amounts to 100% if the *total asset total liability ratio* equals 0.8, that it amounts to 90% if the *total asset total liability ratio* equals 0.9, that it amounts to 50% if the *total asset total liability ratio* equals 1, that it amounts to 10% if the *total asset total liability ratio* equals 1.1, that it amounts to 0% if the *total asset total liability ratio* equals 1.2, and that it amounts to 0% if the *total asset total liability ratio* equals 2.

The *liquid asset liquid liability ratio* is of course equal to the amount of *liquid assets* over the amount of *liquid deposits and loans*. And the *total asset total liability ratio* equals the sum of the *fixed assets* and the *liquid assets* over the sum of the *liquid deposits and loans* and the *fixed deposits and loans*.

The central bank issues a *bank failure declaration* (forcing a bank into bankruptcy) if the *liquid asset liquid liability ratio* falls below 0.05 or the *total asset total liability ratio* falls below 0.9.

B.2 Case Questions

1. (/8) Make a System Dynamics simulation model of this issue on your computer. Verify the model. Save the model.
2. (/1) Simulate the model first of all over a time horizon of about 60 days without any anger or an 'organised' bank run. In other words, set *anger* equal to 0, *concerted liquid fraction running away away* equal 0%, and the *credibility of the denials* equal to 90%. Make graphs of *liquid deposits and loans lost* and the *perceived likelihood of a bank failure.*
3. (/5) Now, adapt the model to simulate a bank run following Pieter Lakeman's call for an concerted bank run. Suppose for example that the *concerted liquid fraction running away* jumps to 5% on day 2 and falls down to 0% on day 4 and that the *credibility of the denials* falls from 90% to 10% from day 2 on. Suppose also that on top of these changes the variable *anger* amounts to 0.5 and the *liquidation premium* to 25%. Save the model.
   (a) Simulate the model over a time horizon of 60 days. Make graphs of *liquid deposits and loans lost* and the *perceived likelihood of a bank failure.*
   (b) Explain the behaviours obtained, especially if you obtain strange behaviours.
   (c) Briefly describe whether and what the bank could do to prevent this bank run.
4. (/3) Simulate a bad case scenario, again over a time horizon of 60 days, in which *anger* is 1, *hindrance of bank failures* is 1, and the *liquidation premium* is 25%.
   (a) Make graphs of the *liquid deposits and loans lost* and *perceived likelihood of a bank failure.*
   (b) Briefly describe the differences with the previous behaviour?
   (c) Briefly describe whether and what the bank could do to prevent this bank run.
5. (/1) Validate the model extremely briefly. Use maximum 2 (different) validation tests. List the tests used and briefly describe the conclusions of the tests.
6. (/4) Draw a *causal loop diagram* of the system to help you communicate the main feedback effects responsible for the bank run.
7. (/1) Explain the link between structure & behaviour briefly (e.g. for the 'bad case' scenario).
8. (/1) Save your model again and add a simple closed loop policy (in colour) that prevents the bank from collapsing. Describe the policy briefly. Test the policy at least in case of the 'bad case' scenario and sketch the resulting dynamics on your exam copy.
9. (/1) How do we call variables like *hindrance of bank failures* and *anger*?

C ESDMA Results

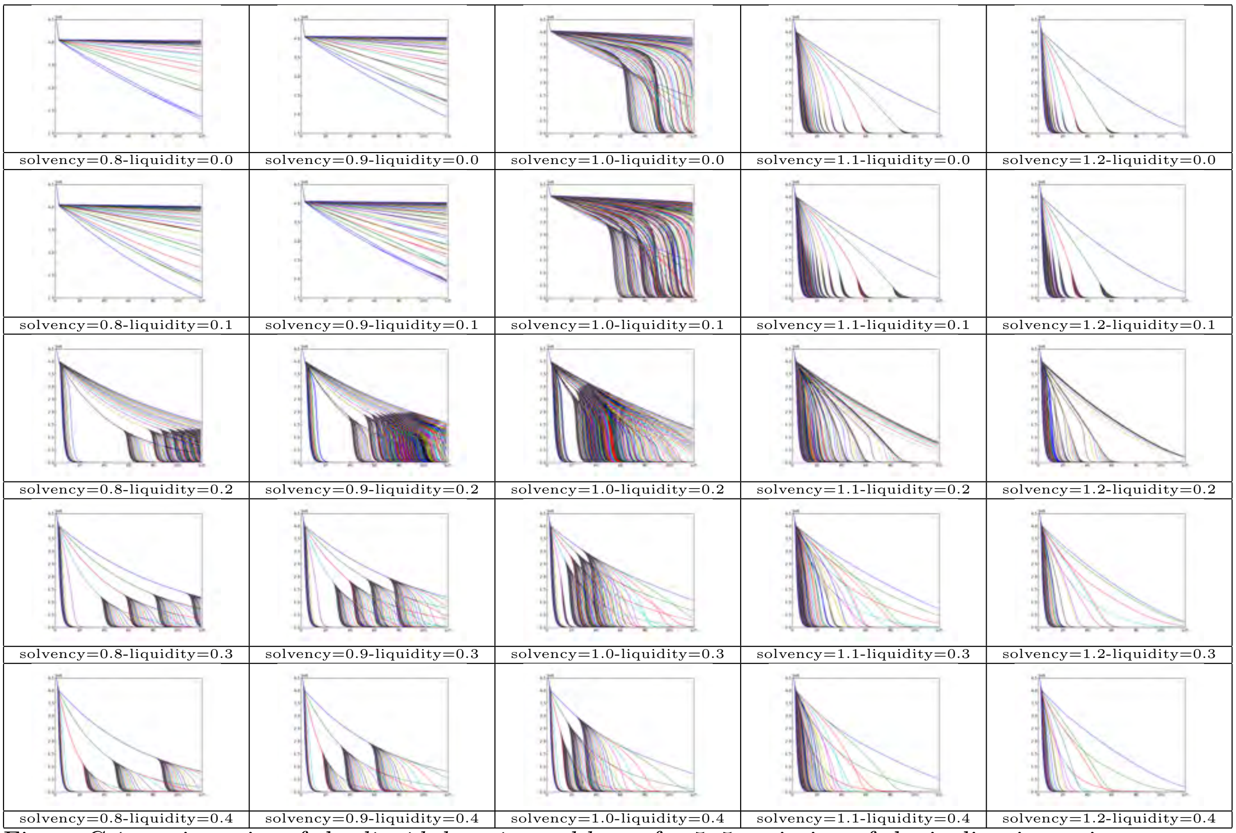

Figure C.1: trajectories of the *liquid deposits and loans* for 5x5 variation of the inclination points of the solvency and liquidity functions, with 900 (full factorial) samples of the skewness of these functions per graph

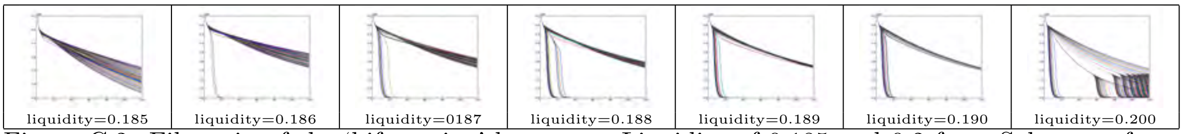

Figure C.2: Filmstrip of the 'bifurcation' between a Liquidity of 0.185 and 0.2 for a Solvency of 0.8 (first column of table C.1)

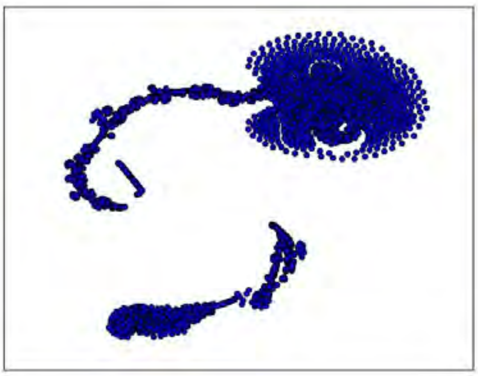

Figure C.3: Two-dimensional resemblance plot of 5000 out of 40000 EMA trajectories indicating the existence of structures in the data

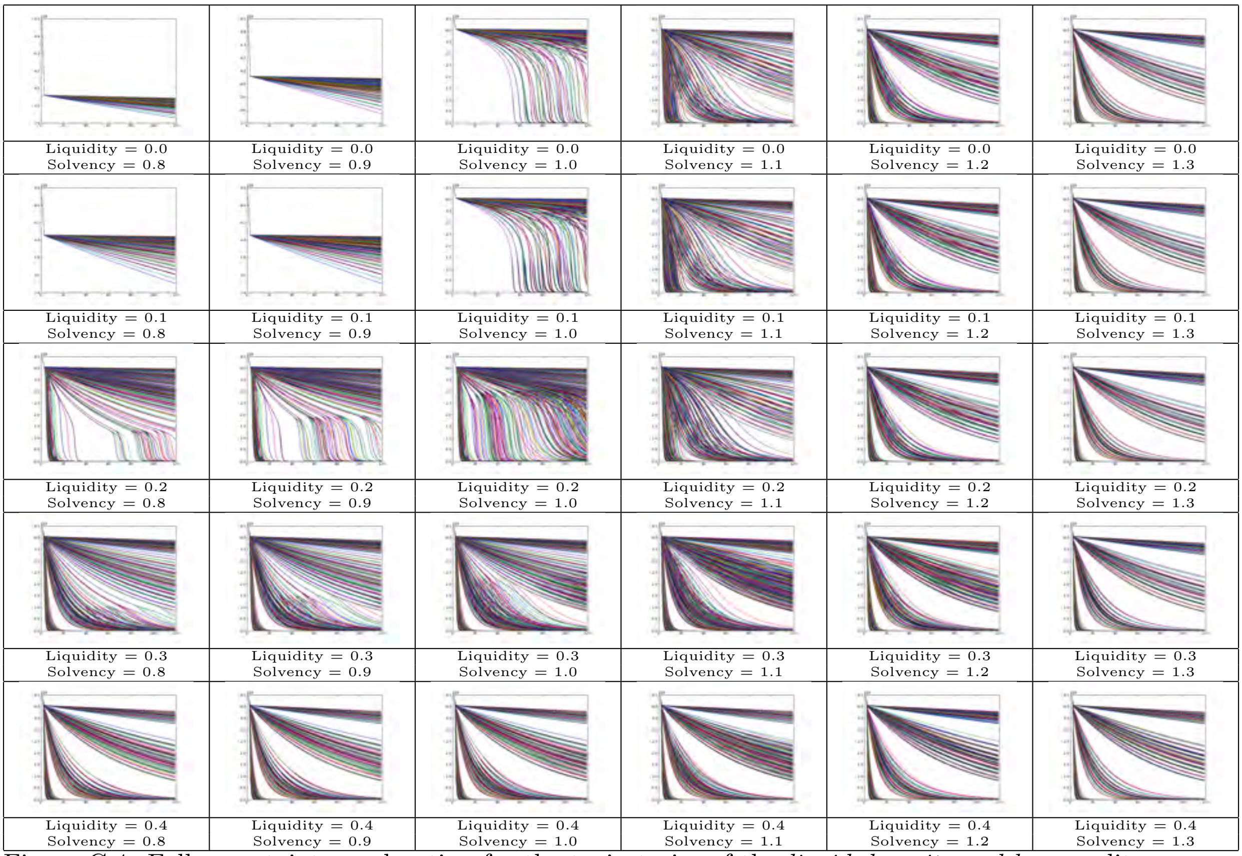

Figure C.4: Full uncertainty exploration for the trajectories of the *liquid deposits and loans* split out in 25 graphs according to combinations of the inflection points of the *perceived likelihood of liquidity failure* and *perceived likelihood of solvency failure* functions