Liquidity Stress-Tester
A model for stress-testing banks' liquidity risk

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Abstract

This paper presents a stress-testing model for liquidity risks of banks. It takes into account the first and second round (feedback) effects of shocks, induced by reactions of heterogeneous banks, and reputation effects. The impact on liquidity buffers and the probability of a liquidity shortfall is simulated by a Monte Carlo approach. An application to Dutch banks illustrates that the second round effects in specific scenarios could have more impact than the first round effects and hit all types of banks, indicative of systemic risk. This lends support policy initiatives to enhance banks' liquidity buffers and liquidity risk management, which could also contribute to prevent financial stability risks.

Key words: banking, financial stability, stress-tests, liquidity risk

JEL Codes: C15, E44, G21, G32

1. Introduction

The recent financial crisis has underscored the need to explicitly take into account liquidity risk in stress-testing frameworks. The manifestation of liquidity risk can rapidly move the system into the tail of the loss distribution through bank runs, the drying up of market liquidity or doubts of counterparties about banks' liquidity conditions. In these situations liquidity can evaporate, making a bank subject to multiple possible equilibria with very different levels of liquidity supply (Banque de France, 2008). Liquidity risk is not only a source of banks' funding risk (the ability to raise cash to fund the assets), but also has a strong link to market liquidity (the ability to convert assets into cash at a given price). The originate-to-distribute model has made banks increasingly dependent on market liquidity to secure funding by issuing securities on wholesale markets and by trading credits. As a result, banks have become more vulnerable to macroeconomic and financial shocks that may engender liquidity risk.

Various regulatory initiatives in response to the credit crisis have highlighted that banks' stress-testing practices usually do not incorporate liquidity risk scenarios sufficiently (FSF, 2008). Banks often underestimate the severity of market-wide stress, such as the disruption of several key funding markets simultaneously (e.g. repo and securitisation markets). Moreover, banks do not systematically consider second-order effects that can amplify losses. These can be caused by idiosyncratic reputation effects and/or collective responses of market participants, leading to disturbing (endogenous) effects on markets. Banks have insufficient incentives to insure themselves against such risks (FSA, 2007). This is because holding liquidity buffers is costly and may create a competitive disadvantage. Besides, liquidity stresses have a very low probability and market participants could have the perception that central banks will intervene to provide liquidity in stressed markets.

Macro stress-testing, i.e. testing the financial system as a whole, is an instrument of central banks and supervisory authorities to assess the impact of market-wide scenarios and possible second round effects. Such tests with regard to liquidity risk can enhance the insight in the systemic dimensions of liquidity risk. These exercises can also contribute to market participants' awareness of systemic risks. However, liquidity risk is not included in most macro stress-testing models. A main reason for this is that the multiple dimensions of liquidity risk make quantification difficult (IMF, 2008). This could also explain the large variation in the extent to which supervisors prescribe limits on liquidity risk and insurance that banks should hold (BCBS, 2008).

This paper presents a stress-testing model which focuses on both market and funding liquidity risk of banks. Multiple dimensions of liquidity risk are combined into a quantitative measure. Section 2 describes related models by reviewing the literature. Section 3 outlines the model framework of Liquidity Stress-Tester and explains the model structure for the first and second round effects of shocks to banks' liquidity. It also provides a parameter sensitivity analysis Section 4 presents model simulations for Dutch banks as an illustration, including an anecdotal back test. Section 5 concludes.

2. Literature

Our study relates to models of financial intermediation by banks in transmitting and amplifying shocks. For instance, liquidity risk plays a role in the interaction and contagion between banks in the interbank market. Upper (2006) presents a survey of interbank contagion models, concentrating on interbank loans. This channel of contagion is operative when banks become insolvent due to defaults by their (interbank) counterparties. Contagion may also take the form of deposit withdrawals due to fears that banks will not be able to meet their liabilities because of losses incurred on their (interbank) exposures. Upper sees scope for improvements in the specification of the scenarios leading to contagion. He concludes that a fundamental shortcoming is the absence of behavioural foundations of the interbank contagion models, which results in the assumption that banks do not react to shocks (i.e. absence of optimising banks). Adrian and Shin (2008) add to this that domino models do not take sufficient account of how prices change. Related to interbank contagion studies is literature that analyses payment and settlement systems as a potential source of liquidity shocks and contagion between banks (see for instance Leinonen and Soramäki, 2005). Some studies in this field also pay attention to behavioural reactions (e.g. Bech et al, 2007, Ledruth, 2007).

Recent work provides some more guidance on how micro foundations could be introduced into financial sector models. The model of Goodhart et al (2006) is based on both heterogeneous banks and households (investors) and operates through endogenous feedback mechanisms, both amongst banks, investors and between the real and financial sectors. Liquidity indirectly plays a role through the credit supply of banks to other banks and consumers, while default is endogenous within the system. A drawback of their model is the simplification of the economy to only banks and consumers. Furthermore, the authors recognise the challenge of their approach to reflect reality. Aspachs et al (2006) have calibrated the Goodhart model to values of several banking systems by using the probability of default of banks as a measure of financial fragility.

Another strand of models links the banking sector to asset markets, which differs from earlier studies that view liquidity shortages as stemming from the bank’s liability side, due to depositor runs (e.g. Allen and Gale, 2000) or withdrawals of interbank deposits (Freixas et al, 2000). Goetz von Peter (2004) relates banks and asset prices in a simple monetary macroeconomic model in which asset prices affect the banking system indirectly through debtors’ defaults. Asset price movements that are driven by market liquidity can also lead to endogenous changes in banks’ balance sheets through a financial accelerator (Adrian and Shin, 2007). Cifuentes et al (2005) examine how defaults across the interbank network are amplified by asset price effects. Herein, market liquidity drives the market value of banks’ assets which in a downturn can induce sales of assets, depressing prices and inducing further sales. Nier et al (2008) apply the same mechanism to an interbank network in which contagion is dependent on the connectivity, concentration and tiering in the banking sector. In this framework the default dynamics with liquidity effects are simulated, including second round defaults of banks. These result from shocks to the assets of banks, rather than to the liabilities. The model of Diamond and Rajan (2005) also focuses on the bank's asset side and shows that a shrinking common pool of liquidity exacerbates aggregate liquidity shortages. Boss et al (2006) have developed a system in which models for market and credit risk are brought together and connected to an interbank network module. This is similar to the framework developed by Alessandri et al (2008), which also takes into account asset-side feedbacks induced by behavioural responses of heterogeneous banks. These two models are used for stress-testing by the Oesterreichische Nationalbank and the Bank of England, respectively. Off-balance contingencies are not covered in these models. Feedback effects arising from market and funding liquidity risk are also (still) missing in most macro stress-testing models of central banks. Such effects are featuring in models with margin constrained traders, as in Brunnermeier and Pedersen (2007). They model two 'liquidity spirals', one in which market illiquidity increases funding constraints through higher margins and one in which shocks to traders funding contributes to market illiquidity due to reduced trading positions.

Our approach relates to the last strand of work, but while the study of Brunnermeier and Pedersen is mainly conceptual in nature, our model is based on a more mechanical algorithm to make it operational for simulations with real data. In this respect, Liquidity Stress-Tester belongs to the class of simulation models of central banks that are used to quantify the impact of shocks on the stability of the financial system. The value added of our approach is the focus on the liquidity risk of banks, taking into account the first and second round (feedback) effects of shocks, including price effects on markets, induced by behavioural reactions of heterogeneous banks and idiosyncratic reputation effects. The model centres on the liquidity position of banks and their related risk management reactions. The contagion channels through which the banks are affected (e.g. the interbank network, asset markets) are not explicitly modelled. Instead, contagion results from the effects of banks' reactions on prices and volumes in the markets where other banks are exposed to, as described in the next section.

3. Model

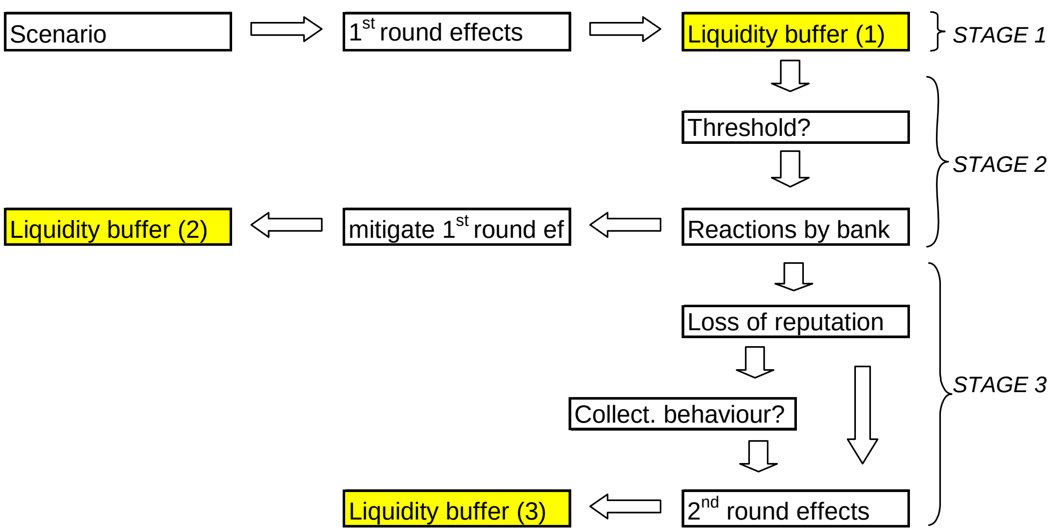
3.1 Framework

In stylised form the Liquidity Stress-Tester model can be represented by Figure 1a. Banks' liquidity positions are modelled in three stages; after the first round effects of a scenario, after the mitigating actions of the banks and after the second round effects. In each stage, the model generates distributions of liquidity buffers by bank, including tail outcomes and probabilities of a liquidity shortfall. The model is driven by Monte Carlo simulations of univariate shocks to market and funding liquidity risk factors which are combined into a multifactor scenario. For instance, a credit market scenario can be assumed to include rising credit spreads, falling market prices of structured credit securities (market liquidity) and reduced liquidity in the primary markets for debt issues (funding liquidity). The model is flexible to choose any plausible set of shock events. This deterministic approach of scenario building is based on economic judgement and historical experiences of confluences of events that are likely to lead to a banking liquidity crisis. In the model the scenario horizon is set at one month but the model is flexible to extend it (as an example, section 4.2 presents outcomes at a horizon of 6 months).

A scenario is uniformly applied to individual banks by weighting the banks' liquid asset and liability items (*i*) that would be affected by the scenario with stress weights (w_i). For instance, in case of the credit market scenario, weights would be attached to banks' tradable credit portfolios, collateral values and wholesale funding liabilities. The weights (w_i) stand for haircuts in the case of liquid assets (reflecting reduced liquidity values or mark-to-market losses) and run-off rates in the case of liabilities (reflecting the drying up of funding). The size of the weights w_i differs per balance sheet item according to the varying sensitivity of assets and liabilities to liquidity stress (see section 3.2).

In the model, a scenario is assumed to unroll in two rounds. In the first round the initial effects of shocks to banks' market and funding liquidity risks are modelled (stage 1 of the model, represented by the first line of the flow chart in Figure 1a). This is done by multiplying the liquid asset and liability items that are affected in the first round of the scenario by the stress weights (w_i). The resulting loss of liquidity is then subtracted from a banks' initial liquidity buffer. The outcome is given by 'liquidity buffer (1)' in the Figure and is in fact a distribution of buffer outcomes per bank, following from the simulated market and funding liquidity risk events (i.e. the simulated stress weights, w_i).

Figure 1a, flow chart of **Liquidity Stress-Tester**

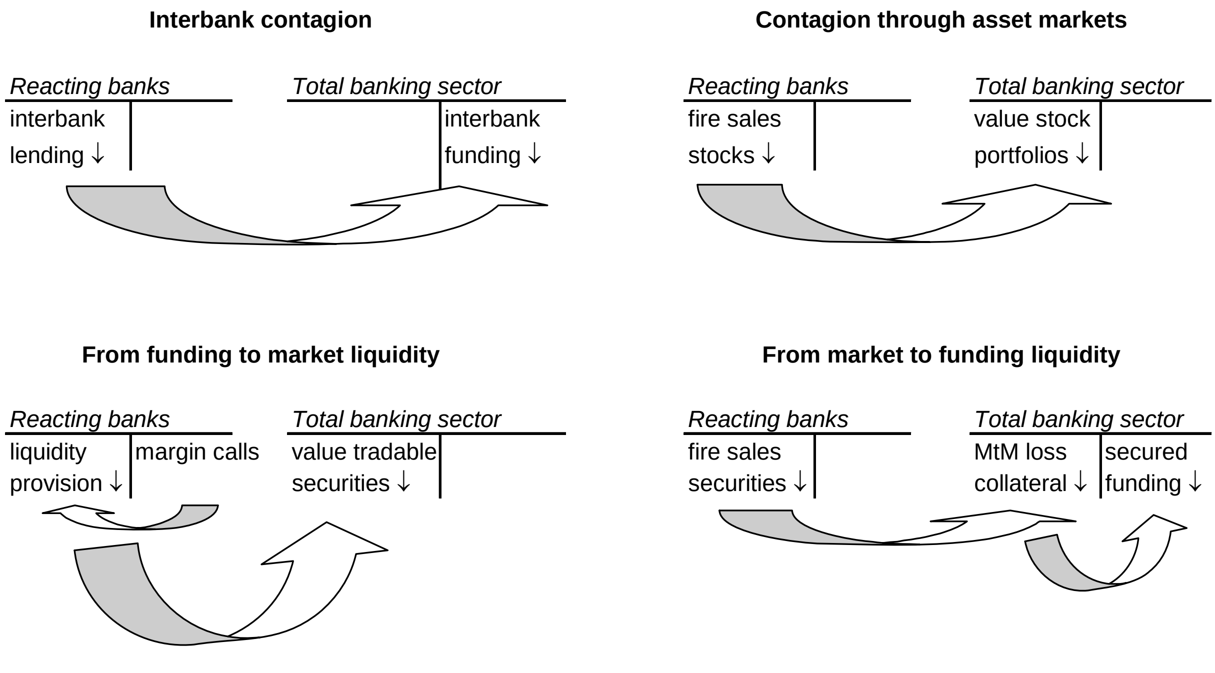


The second stage of the model entails the mitigating actions of the banks in response to the shocks in the first round of the scenario. Their responses are assumed to be triggered if the decline of the liquidity buffer due to the initial shocks breaches a predefined threshold, which reflects a significant impact (the threshold for reactions is derived in section 3.4). The reacting banks take mitigating measures to mobilise liquidity and restore their liquidity buffers (resulting in the improved 'liquidity buffer (2)' at the end of the second line of the flow chart). The type of measures by which the banks react (i.e. the markets in which they operate) are defined beforehand as part of the deterministic scenario. The reactions of banks set in train the second round effects of the scenario (stage 3 in the model). One part of the second round effect is the idiosyncratic risk of the reacting bank. It faces a reputational risk since it might be perceived to be in trouble by conducting measures to restore its liquidity buffer (signalling effect). The other part of the second round effect is systemic risk. This relates to collective reactions by banks that could lead to wider disturbing effects in the banking sector or on financial markets. Both the idiosyncratic and systemic second round effects of a scenario determine the final liquidity buffer ('liquidity buffer (3)' at the end of the third line of the flow chart).

Liquidity Stress-Tester takes into account that systemic risk turns out to be larger if i) more banks would react, since collective reactions are more disturbing, ii) reactions would be more similar, taking into account possible distortions by 'crowded trades' and iii) reacting banks are larger, since reactions by sizable banks are more likely to cause market-wide instability. For instance in the case of a credit market scenario, if large banks would collectively react to the initial shocks by withdrawing interbank credit lines and by fire sales of certain assets, dislocations in the unsecured interbank markets and distressed market prices in particular market segments are likely. In the model, both the idiosyncratic loss of reputation and the wider systemic effects have an impact on banks' liquidity buffers through additional haircuts on liquid assets and withdrawals of liquid liabilities (i.e. the second round effects further increase the stress weights, w_i of the affected balance sheet items).

The systemic second round effects embody contagion within the banking sector as well as interactions between markets and banks. The contagion results from the effects of banks' reactions on the prices and volumes in the markets where the banking sector is exposed to (possible market stress caused by other developments is included in the model as an exogenous variable). For instance if banks would react to restore their liquidity position by cutting credit lines to other banks, which could be a defined reaction in the scenario, the banking sector experiences reduced funding liquidity in the interbank market (this type of second round effect is depicted in the upper left panel of Figure 1b). In the model, the effect on interbank exposures does not operate directly through mutual balance sheet linkages as in traditional interbank contagion models, but indirectly through a reduced liquidity in the interbank market as a whole (reflected in a stress weight (w_i) applied to interbank liabilities). This is assumed to be an aggregate effect; the model does not specify whether it relates to increased borrowing rates or reduced credit supply. The same applies to contagion through interlinkages between markets and banks. For instance, if banks would react to restore their liquidity position by fire sales of stock portfolios, which could be a reaction defined in the scenario, the banking sector as a whole is affected by reduced mark-to-market values of stocks. This shows up in a stress weight (w_i) applied to the stock portfolios of banks (this type of second round effect is depicted in the upper right panel of Figure 1b). Possible interactions between market and funding liquidity, as explored in IMF (2008), are also taken into account in the model framework. For example, funding pressures due to margin calls may lead to reduced liquidity provision by banks to investors. This will strain the trading activity on financial markets and give rise to falling market prices, affecting the banks with exposures to the pressed tradable securities. In the model this is accounted for by applying a stress weights (w_i) to the affected securities holdings of the banks (see lower left panel of Figure 1b). Contagion can also run from liquidity shocks on markets to funding liquidity, as depicted in the lower right panel of Figure 1b. This could be the case if banks are forced to sell tradable securities in response to an initial shock, engendering falling market prices and reduced collateral values. The latter will strain the funding possibilities of banks in the repo market. In the model this is reflected in a stress weight (w_i) applied to repo funding lines.

Figure 1B, Systemic effects through contagion channels



3.2 Data

While Liquidity Stress-Tester is a top-down model, it is run with bank level data. In case of the Dutch banks, we use the liquidity positions (both liquid stocks or non-calendar items and cash flows or calendar items) that are available from DNB's liquidity report on a monthly basis. Data include on and off-balance sheet items. As baseline, the model assumes a going concern situation, as reflected in unweighted liquid assets and liabilities. This assumes that liabilities can be fully refinanced and that the liquidity value of assets is 100%., i.e. the weights (w_i) are 0.

The weights are taken from DNB's liquidity report in which they are fixed values (DNB, 2003). In the report, the actual liquidity of a bank must exceed the required liquidity, at both a one week and a one month horizon. By this, the report tends to focus not only on the very short term, but also on the more structural liquidity position of banks. In the report, actual liquidity is defined as the stock of liquid assets (weighted for haircuts) and the recognised cash inflow (weighted for their liquidity value) during the test period. Required liquidity is defined as the assumed calls on contingent liquidity lines, assumed withdrawals of deposits, drying up of wholesale funding and liabilities due to derivatives. In this way, the liquidity report comprises a combined stock and cash flow approach. The weights (w_i) applied to the liquid assets and liabilities in the DNB report represent a mix of a firm specific and market wide scenario and are based on best practices and values of haircuts on liquid assets and withdrawal or run-off rates of liabilities typically used by the industry and rating agencies (see Table A in the Annex)[1]. This makes them a useful point of departure for our model. The parameterisation of the run-off rates, either based on best practices or historic data, is a weakness in most liquidity stress-testing models of banks. This is because data of stress situations are scarcely available and in times of stress the assumed elasticities may behave differently. As a consequence, banks' may underestimate the stability of their funding base. By applying a stochastic approach, Liquidity Stress-Tester takes into account this uncertainty of the model parameters.

3.3 First round effects

In Liquidity Stress-Tester the fixed weights of DNB's liquidity report are assumed to be 0.1% tail events[2] ($w_i \approx 3 \text{ x } \sigma$). The scenario impact of the first round effect on an item i is determined by simulated weights ($w\_sim_{1,i}$). These are based on Monte Carlo simulations by taking random draws from a normal distribution N (0,1), that is scaled by (w_i / 3). The scaled normal distribution is then transformed to a log-normal distribution by Exp (N (0,1) * (wi / 3))[3], so that $w\_sim_{1,i}$ ~ Log-N (μ,σ^2). The use of a log-normal distribution is motivated by the typical non-linear features of extreme liquidity stress events. The log-normal distribution, which is skewed to the right, captures this feature. Its asymmetric shape fits well on financial market data in particular in high volatility regimes. For that reason the log-normality of asset returns plays an important role in theory of risk management and asset pricing models. Besides, the log-normal distribution is bounded below by 0 which is also due for

[1] In the model, the weights of DNB's liquidity report that apply to a horizon of 1 month are used.
The liquidity model of Standard & Poor's (2007) is based on a standard set of assumptions, i.e. a spectrum of asset haircuts and liability run-off rates, that were established after a review of bank balance sheets, industry, S&P data and dialogue with risk managers.

[2] In the model simulations this assumption could be changed according to other insights.

[3] This transformation is based on the fact that if X ~ N (μ,σ^2) is a normal distribution then Exp (X) ~ Log-N (μ,σ^2).

the simulated weights in our model. As an upper bound, the weights are truncated at $w\_sim_{1,i} \leq 100$ in the simulations, since haircuts and withdrawal rates can not exceed 100%. This procedure delivers a log-normal distribution of weights which is bounded below by 0 and truncated at the top by 100. The liquidity buffer in the baseline situation (normal market conditions), B_0, is

$$B_0^b = \sum_{i=1}^{nc} I^b_{non-cal,i} \tag{1}$$

b being the individual bank and $I_{non-cal,\,i}$ the amount of available assets of non-calendar items (the stock items of liquid assets *1 .. nc*). By this, the buffer is made up by deposits at the central bank, securities that can be turned into cash at short notice, ECB eligible collateral, interbank assets available on demand and receivables from other professional money market players available on demand. B_0 provides counterbalancing capacity to liquidity scenarios in which liquidity values of the stock of assets could decline and a drain of liquidity could occur due to decreasing net outflows of liquidity. This means that the scenario effects could be felt through both deteriorating liquid stocks and flows. The first round effect (E_1) of the scenario is determined by,

$$E_1^b = \sum_i I_i^b \times w\_sim_{1,i} \tag{2}$$

I_i being the amount of all liquid (non-calendar and calendar) asset and liability items. The liquidity buffer after the first round impact of the scenario, B_1, is,

$$B_1^b = B_0^b - E_1^b \tag{3}$$

3.4 Banks' response to scenario (mitigating actions)

Banks that are affected seriously by the first round effects of the scenario are assumed to react to restore their liquidity buffer to the initial level (B_0). Banks may take actions to safeguard their stability and/or to meet liquidity risk criteria of supervisors and rating agencies. In the model, the trigger for a bank's reaction is a decline of its original liquidity buffer that exceeds a threshold θ. By this, reactions are triggered by a significantly large impact of the first round of the scenario (as reflected in the simulated buffer B_1). The trigger q (0, 1) is based on a probability condition (probit),

with $q = \begin{cases} 1 \;\; if \;\; \dfrac{E_1^b}{B_o^b} > \theta \\ 0 \;\; otherwise \end{cases}$

The latent variable θ can be seen as a 'rule measure' which banks follow due to self imposed liquidity risk controls or regulatory requirements. The rule is operationalised by assuming that large value change of balance sheet items reflect banks' intentional responses to a buffer decline. The rule variable θ can then be derived from the average correlation between value changes of balance sheet items and declines of liquidity buffers one month lagged:

$$Correl\left(\frac{B^b_{t=0}-B^b_{t=-1}}{B^b_{t=-1}},\frac{I^b_{i,t=1}-I^b_{i,t=0}}{I^b_{i,t=0}}\right)\text{, conditioned by }\frac{B^b_{t=0}-B^b_{t=-1}}{B^b_{t=-1}}<0$$

The lag controls for the influence of possible endogeneity in the relationship between the buffers and the balance sheet items. In an empirical application for the Dutch banking sector the correlation coefficient has been computed with data of 82 Dutch banks and 80 monthly periods, covering 2001-4 to 2007-12.[4] Table 1 shows that only substantial declines of the liquidity buffer (from 40%) lead to significant changes of balance sheet items in the next period. This only indicates whether a bank would react and not the direction of the response.[5] Smaller declines are probably (passively) absorbed by the buffers of the banks. Based on this outcome, a rule variable θ equal to 40% is used as a uniform trigger for each banks' reaction.

Table 1
Correlation between relative change of buffer (B), lagged relative change of balance sheet items (I)
Spearman correlation coefficient

Buffer change (%)	obs	Correl
0 - 10	25453	-0.00015
10 - 20	8303	0.00285
20 - 30	3437	0.00218
30 - 40	1892	-0.00163
40 - 50	1134	-0.05615 *
50 - 60	767	0.01756
60 - 70	681	0.07847 **
≥ 70	617	0.0291

***, **, * significant at 1%, 5%, 10% confidence level
Based on 82 Dutch banks, 80 months, around 7 items per bank on average
Source: own calculations based on DNB liquidity report.

The type of instruments (items *i*, amounting *I*) which banks use to react is specified beforehand in the design of the second round of the scenario, based on judgement of the set of instruments that will most likely be used in a particular scenario. For instance banks can use securities eligible for repo with central banks, draw on liquidity lines from other banks, sell liquid securities, such as government bonds or asset backed securities, or rely on unsecured funding in the (money) markets. The choice of instruments may be determined by internal rules or contingency funding plans that sometimes

[4] The assumption that the change of I_i reflects balance sheet adjustments is quite strong as changes of I_i could also be caused by exogenous price movements. However, very large changes of I_i are more likely to be caused by portfolio adjustments since extreme price effects on a 1 month period of time can be considered quite rare. Moreover, banks do not value all the balance sheet items on a mark-to-market basis. $B_{t=0} \neq B_0$ and $B_{t=1} \neq B_1$, as the former are the actual monthly buffers, whereas the latter are the buffer in each stage of the model simulations.

[5] Hence the sign of the correlation coefficients can not be interpreted straightforward since the value of items can either increase or decrease in reaction to declines of the buffer, depending on the type of crisis, the nature of the balance sheet item and the response of the individual bank. For instance, to generate liquidity a bank can either sell tradable securities (value of asset item decreases) or issue additional securities (value of liability item increases), or substitute some assets of liabilities with other items.

prescribe different sets of measures for various scenarios. Regulators promote the linkage of stress-tests to contingency funding plans (FSF, 2008).

In the model, the extent to which banks use particular instruments to restore the liquidity buffer is assumed to be (mechanically) determined by the relative importance of items on the balance sheet ($I_i^b / \sum_i I_i^b$), reflecting a bank's specialisation and presence in certain markets.[6] Since in liquidity crises time as usually very short, banks often do not have the opportunity to change their strategy (e.g. by diversifying funding or spreading risk). The size of the transactions that a bank conducts with instrument *i* is expressed by RI_i^b,

$$RI_i^b = (B_0^b - B_1^b) \times (I_i^b / \sum_i I_i^b) \tag{4}$$

Since $B_1 \leq B_0$, by definition RI_i^b is positive. This does not imply anything about the direction of the transaction (e.g. buying or selling) but it indicates the (absolute) size of the transaction that is needed to generate liquidity (RI_i^b is a size factor). Hence, the liquidity buffer after the mitigating actions (B_2) of a bank is equal to,

$$B_2^b = B_1^b + \sum_i RI_i^b \times (100 - w\_sim_{1,i}) \tag{5}$$

with $B_2 > B_1$, but $B_2 < B_0$, since the buffer can not be fully restored due to the market disturbances in the first round of the scenario (as reflected in $w\_sim_{1,i}$). In an extreme stress situation, financial markets may be gridlocked completely due to the drying up of liquidity. Such an extreme case is represented by $w\_sim_{1,i}$ = 100, implying that banks have no possibility to enter a particular market segment to raise additional liquidity. In the case of the repo markets this could mean that certain collateral of banks may be useless.

3.5 Second round effects

The behavioural reactions of the banks can have wider disturbing (endogenous) effects on markets, feeding back on the banks. This will be manifested in additional haircuts on liquid assets and withdrawals of liquid liabilities in the market segments where banks react, as reflected in $w\_sim_{2,i}$ (with $w\_sim_{1,i} \leq w\_sim_{2,i} \leq 100$). The feedback effects are larger if more banks would react ($\sum_b q$) *and* if reactions would be more similar, which is expressed by the sum of reactions by a particular instrument ($\sum_b RI_i^b$). This summation is divided by the total amount of reactions $(\sum_i \sum_b RI_i^b)$ to get the ratio that indicates the similarity of reactions ($\sum_b RI_i^b / \sum_i \sum_b RI_i^b$). In the case of deep and liquid

[6] The model does not specify the conditions (e.g. credit spreads) at which funding is attracted.

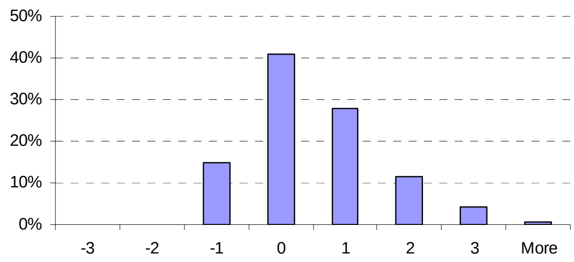
markets (e.g. the government bond market) where discretionary transactions will have little effects, $w\_sim_{2,i}$ is smaller than in the case of illiquid market segments. Such differences will already be reflected in $w\_sim_{1,i}$ from which $w\_sim_{2,i}$ is derived,

$$w\_sim_{2,i} = w\_sim_{1,i} \times \left(\sum_b q \,\hat{}\,\left(1+\sum_b RI_i^b / \sum_i \sum_b RI_i^b\right) \times s\right) / \sum_b q \tag{6}$$

Since RI_i^b indicates the size of the transaction that is conducted to generate liquidity, higher values of RI_i^b imply a higher liquidity demand, which will adversely affect the availability of liquidity in market segments in which the banks operate. By including RI_i in equation 6, large transactions have more impact on markets than small transactions. This implicitly means that reactions by large banks induce stronger second round effects than reactions by small banks.[7] Equation 6 compares to the relationship between asset prices and sales of assets by banks as used by Alessandri et al, 2008 and Nier el al, 2008. In their models, the price of banking assets is a decreasing function of liquidated assets and the elasticity of the price effects which they refer to as a measure of market illiquidity. In our model, the latter is both included in $w\_sim_{1,i}$ and s, being a state variable which represents the exogenous market conditions.

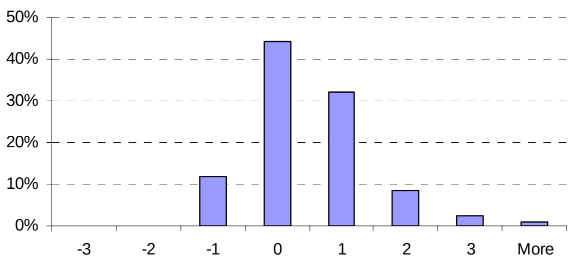
More in particular, the state variable s represents an indicator of market stress. The ranges of this variable are derived from standardised distributions of risk aversion indicators. For this the implied stock price volatility (VIX index) and the US corporate bond spreads (Baa) were used as proxies. Figures 2a and 2b show standardised frequency distributions of these series. To determine a range of s for use in the model, we assume that normal market conditions are reflected by $-1 \leq s \leq 1$ (which according to a standardised distribution of risk indicators represents 2/3 of market conditions) and severe market stress by $s = 3$ (i.e. 0.05% of adverse market situations). s could be even higher, as Figures 2a and 2b indicate. For the purpose of measuring liquidity stress in the model, the restriction $s \geq 1$ applies. The risk aversion indicators could be used to conduct periodic runs with Liquidity Stress-Tester in which changing market conditions play a role.

Figure 2a Frequency distribution of credit spreads
Normalised value of Moodys Baa average credit spreads on corporate bonds, daily data period 1986-2007



Source credit spreads: US Federal Reserve

Figure 2b Frequency distribution of implied volatility
Normalised value of S&P500 stock price volatility (VIX index), daily data period 1986-2007



Source of VIX: Chicago Board Option Exchange

[7] By running Liquidity Stress-tester with a limited sample of banks (in this paper the Dutch banks) it is implicitly assumed that the reactions of this sample are representative for the (global) banking system as a whole.

In the model, the market conditions contribute to the severity of the second round effects: the higher *s*, the stronger are the effects of the number and the similarity of banks' reactions. Figures 3a and 3b illustrate the relationship between $w\_sim_{2,i}$ and $w\_sim_{1,i}$ and its dependence on the number of reacting banks ($\sum_b q$), the similarity of reactions ($\sum_b RI_i^b / \sum_i \sum_b RI_i^b$) and the level of market stress (*s*).

It is assumed that the similarity of reactions has a stronger effect on markets than the number of reacting banks (see the exponential relationship in Figure 3b). The intuition behind is that the similarity of reactions points to crowded trades in markets which cause a drying up of market liquidity.

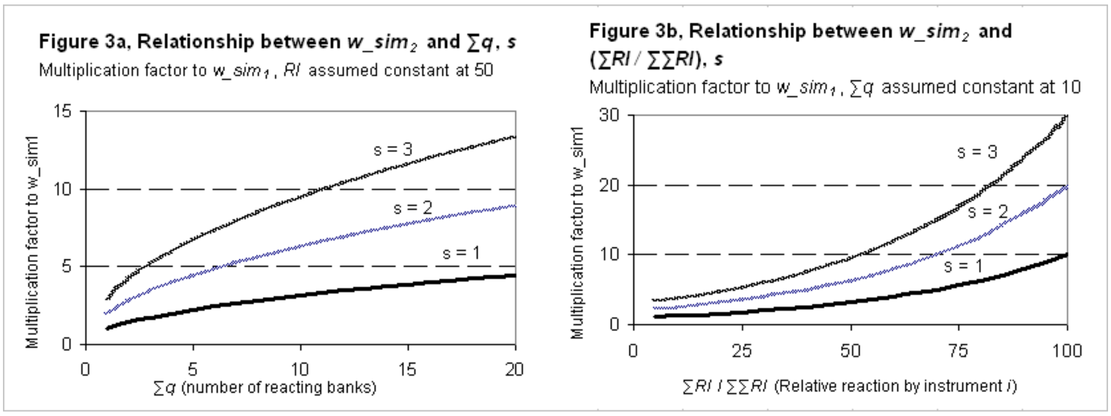


Figure 3a, Relationship between w_sim_2 and $\sum q$, s
Multiplication factor to w_sim_1, RI assumed constant at 50

Figure 3b, Relationship between w_sim_2 and ($\sum RI / \sum\sum RI$), s
Multiplication factor to w_sim_1, $\sum q$ assumed constant at 10

Banks that react in order to restore their liquidity buffer face a reputation risk in the financial markets. While applying sensible measures ought to strengthen a banks' financial position and comfort counterparties, the adverse signalling effect of the transactions could reverberate on the conditions that banks face in the markets. This could translate in even more (idiosyncratic) haircuts on liquid assets and withdrawals of liquid liabilities, as reflected in $w\_sim^*_{2,i}$ (with $w\_sim_{2,i} \leq w\_sim^*_{2,i} \leq 100$). The reputation effect will be dependent on the market conditions (*s*) driving the second round effects, since particularly in stressed circumstances the signalling effect of reactions will adversely feedback on a bank (the stigma associated with accessing central bank standing facilities in the recent crisis is illustrative).[8] In functional form, the reputation risk is expressed by,

$$w\_sim^*_{2,i} = w\_sim_{2,i} \times \sqrt{s} \tag{7}$$

Next, the additional impact of the (systemic and idiosyncratic) second round effects on banks is determined by E_2,

$$E_2^b = \sum_i ((I_i^b + RI_i^b) \times (w\_sim_{2,i} - w\_sim_{1,i})) \tag{8}$$

[8] Equation 7 has been calibrated on the actual outcomes of the individual banks and on the share of the reputational effect in the total second round effect (see section 4). If $s = 1$ (the downside restriction for *s*), than the mitigating reaction of a bank will not be counteracted by adverse reputational effects and will improve a banks' liquidity position by definition.

with $w\_sim_{2,i}$ being replaced by $w\_sim^*_{2,i}$ in case of a reacting bank which also faces reputation risk. The liquidity buffer after the second round effects (B_3) is,

$$B_3^b = B_2^b - E_2^b \tag{9}$$

3.6 Impact different scenario rounds

The stylised balance sheet in Table B of the Annex shows how the model works in a simplified one bank situation. A hypothetical scenario is assumed to affect all liquid assets and liabilities of the bank through fixed in stead of simulated stressed weights. Furthermore, it is assumed that the first round effect of the scenario leads to a decline of the initial liquidity buffer that exceeds the threshold θ and that the bank reacts with all instruments available at its disposal (i.e. asset items 1 and 2 and liability items 1 and 2 on the stylised balance sheet). This example shows that the mitigating actions of the bank improves its liquidity buffer (to B_2), although it remains below the initial level (B_0). The second round effects reduce the buffer further (to B_3), below the level after the first round shock (B_1).

In the stochastic mode of the model, each round of a scenario has its typical effect on the distribution of buffer outcomes. Simulations with real bank data show that the first round effect leads to a shift of the distribution to the left (B_1), while the mitigating actions shift the distribution (B_2) back towards B_0 and cause a peakening of the shape (Figure 4b)[9]. If a bank does not react because $\frac{E_1}{B_0} < \theta$, than the distributions of B_1 and B_2 coincide. This is the case with bank AH in Figure 4a. The second round effect shifts the distribution (B_3) to the left again and causes a flattening of the distribution. The average of this final distribution ($\overline{B}_3$) is substantially smaller than $\overline{B}_1$, which indicates that the second round effects outweigh the initial shock. Such an outcome is conceptually explained by Nikolaou (2009). For the bank which does not face a reputation risk the second round effect is limited. This shows up in a more limited shift of the distribution to the left compared to the reacting bank (see the most left distributions in Figures 4a and 4b).

[9] The parameters of these simulations are equal to those applied in section 4.

Figure 4a, Distribution of buffers after each scenario round
EUR bn, for bank AH as illustration, buffers normalised by B_0 (θ=0.4, s=1.5)

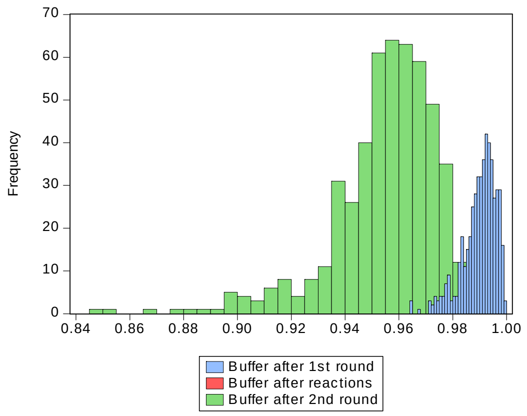
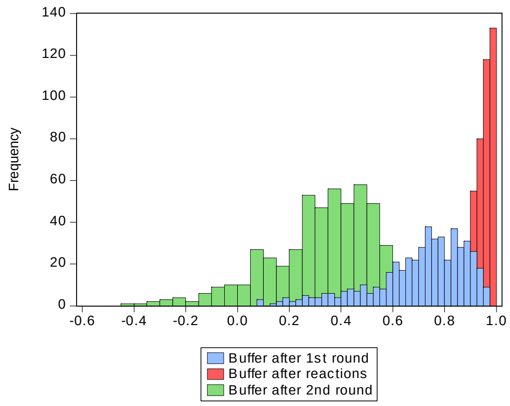


Figure 4b, Distribution of buffers after each scenario round
EUR bn, for bank AU as illustration, buffers normalised by B_0 (θ=0.4, s=1.5)



3.7 Parameter sensitivity

Based on the same stylised balance sheet in Table B in the Annex, this section exposes the sensitivity of the outcomes for changing the model parameters.. In the base line situation, the level of market stress (s) is set at 1.5, the number of reacting banks $(\sum_b q)$ at 2, the similarity of reactions $(\sum_b RI_i^b / \sum_i \sum_b RI_i^b)$ at 0.05 and the scenario horizon at 1 month. Table 2 shows the impact of changing each parameter in isolation on the banks' liquidity buffer, in terms of deviations of the final buffer (B_3) from the initial buffer (B_0). At first sight the model outcomes look relatively sensitive to changes of s (the buffer declines by nearly 2/3 if s = 3) and less to changes in the number of reacting banks and the similarity of reactions (the sensitivity analysis affirms that the latter has a stronger effect on markets than the number of reacting banks). As explained in section 3.5, s reinforces the effects of the number of reacting banks and the similarity of reactions and these factors can hardly be assessed in isolation. Following from equation 7, the impact of reputational risk (due when banks respond to a scenario by mitigating actions) also depends on the level of market stress. Table 2 shows that reputational risk could severely impact on banks in stressed markets. The model outcomes are also quite sensitive to lengthening the scenario horizon; the final buffer declines by ¼ if the horizon is lengthened from 1 to 12 months (which includes the total run-off schedule of liability 1, which is a calendar item).

Table 2, Parameter sensitivity

Impact on average liquidity buffer of bank Y

(percentage change of B_3 compared to B_0 in base line)

	Base line	Changing the parameters (in isolation)			
s	**1.5**	**1**	**2**	**2.5**	**3**
Impact	0%	21%	-21%	-43%	-64%
$\sum q$	**2**	**10**	**20**	**40**	**80**
Impact	0%	-5%	-8%	-10%	-13%
$\sum RI / \sum\sum RI$	**0.05**	**0.2**	**0.4**	**0.6**	**0.8**
Impact	0%	-7%	-18%	-30%	-44%
Horizon (mnt)	**1**	**3**	**6**	**9**	**12**
Impact	0%	-12%	-21%	-23%	-25%
Reputation (Y/N)	**N***	**Y**(s=1.5)**	**Y**(s=2)**	**Y**s=2.5)**	**Y**(s=3)**
Impact	0%	-6%	-27%	-38%	-43%

* Reputational risk has been "switched off" for the purpose of the sensitivity analysis in the base line situation by assuming *s*=1 in equation 7.

** To isolate the impact of reputation risk, *s* is only changed in equation 7.

Stylised balance sheet bank Y (base line)

Assets		*weights*		**Liabilities**		*run-off schedule*					*weights*	
		w_1	w_2			1m	3m	6m	9m	12m	w_1	w_2
asset 1	30	10	16	liab 1 (cal)	11	5	3	2	0.5	0.5	100	100
asset 2	15	30	47	liab 2 (non-cal)	30						5	8
				equity	4							
	45				45							

4. Results

This section describes model outcomes by simulating a hypothetical scenario (a 'classical' banking crisis), and an historical scenario (the recent credit market crisis). These scenarios are run with July 2007 data of all 82 banks in the Netherlands (including subsidiaries of foreign banks). The model outcomes are based on 500 Monte Carlo simulations. In first instance we assume θ = 0.4 (the critical threshold determined in section 3.4), *s* = 1.5 (the middle of the range determined in section 3.5[10]) and a horizon of one month (typically used in banks' liquidity stress-tests). These values are used in the simulations, but can be adjusted to other circumstances (as illustrated in section 4.3). Experimenting with the parameter values enhances the insight in the sensitivity of the model outcomes for banks' reactions, the level of market stress and the length of the scenario horizon.

4.1. Banking crisis scenario

The first round of the hypothetical banking crisis scenario seizes at the liability side of banks' balance sheets. It assumes a public crisis of confidence affecting the banking sector, which could result from massive misselling of a financial product in the retail market. This scenario leads to a withdrawal of

[10] Note that at mid December 2007 during a height of the recent credit crisis, *s* was around 1 as based on corporate bond spreads and around 0.5 as based on implied stock price volatility.

non-bank deposits and other funding by professional money market players, other institutional investors and corporates and by withdrawals of savings deposits by households. These first round effects are simulated by stressing the weights of the affected deposits and funding sources (through $w\_sim_{1,i}$). These weights determine the first round effect (E_1) according to equation 2 and the liquidity buffer (B_1) according to equation 3. Table 3 shows the average outcomes for the 82 banks. On average, the first round effect erases 8% of the initial liquidity buffer. Some small banks would be faced with a negative liquidity buffer after the first round of the scenario.

Table 3 shows that in case of 30 banks, the decline of the liquidity buffer exceeds the threshold $\theta = 0.4$ which triggers them to restore their liquidity buffer to the initial level (B_0).[11] The reactions mitigate the first round effect of the scenario on the sector as a whole to around 7% on average (B_2 being 0.5% smaller than B_0). Figure A.3 in the Annex indicates that smaller banks tend to react relatively more than large banks, which indicates that an outflow of deposits would foremost bring small banks in a critical liquidity position.

In the second round of the scenario it is assumed that banks react to the funding pressures by drawing upon credit lines in the unsecured interbank market. These mitigating actions can be an important source of feedback effects among banks. They are interdependent via interbank liquidity promises and widespread use of these lines will lead to contagion of liquidity risk. The feedback effects ($w\_sim_{2,i}$) are simulated by stressing the weights of the unsecured interbank assets and liabilities. Next to these systemic second round effects, the banks which react by drawing upon liquidity promises of counterparties face a reputation risk since their actions could be perceived as a sign of weakness. In the model simulations this translates into additional (idiosyncratic) stress on the weights ($w\_sim^*_{2,i}$) according to equation 7. Both the reputational risk and the systemic (second round) effects on the markets have an impact on the liquidity buffers of the banks (E_2) according to equation 8 and on the final liquidity buffer (B_3) according to equation 9. Table 3 shows that due to the second round effects the banks additionally loose 6% of their initial liquidity buffers on average (including the effects of mitigation actions). Table 3 also shows the 5% and 1% tail outcomes of the final liquidity buffer and the probability of a liquidity shortfall (i.e. $B_3 < 0$). Insight in the extreme tail outcomes is particularly relevant for financial stability analysis which assesses the resilience of the system to extreme, but plausible shocks. In the 5% (1%) tail the liquidity buffer declines by 26% (32%) on average. Out of the total sample, 25 banks have a probability larger than 0% to end up with a liquidity shortage. These are mostly small banks which explains that the (by the initial liquidity buffer) weighted average probability of a liquidity shortfall is limited to 0.5%. The latter is an indicator of the liquidity risk of the financial system as a whole. Figure A.5 in the Annex indicate a significant negative correlation between the shortfall probability and size of banks, which affirms that small banks are most vulnerable to a ‘classical’ banking crisis scenario.

[11] The Table reports the averages of the simulated buffers, whereas the reactions are triggered by extreme downward changes in the simulated sample of buffers.

4.2. Credit crisis scenario

The first round of the credit crisis scenario seizes at the asset side of banks' balance sheets. It is designed by assuming declining values of banks' tradable credit portfolios, due to uncertainties about the asset valuations which cause a drying up of market liquidity. The falling collateral values lead to higher margin requirements on banks' derivative positions. These first round effects are simulated by stressing the weights of the credit portfolios and margin requirements (through $w\_sim_{1,i}$). Table 3 shows the average outcome for the 82 banks. On average, the first round effect erases 13% of the initial liquidity buffer, with a maximum of 92% for the bank that is most severely affected. Although most banks would be affected by the scenario (i.e. $B_1^b < B_0^b$), the liquidity buffers of the affected banks would remain in surplus in all cases. The banks that are not affected at this stage of the scenario are mostly small branches of foreign banks. They could count on liquidity support from the head office and probably therefore do not hold eligible collateral. A break-down of the sample by bank size and funding structure indicates that banks with a more diversified funding profile are relatively more vulnerable to the first round of the scenario (see Figure A.8 in Annex, Figure A.7 indicates that there is no significant correlation with bank size). Although a more diversified funding profile in general improves banks' resilience to liquidity shocks, the fact that the recent crisis has been most felt in the international financial markets has raised the vulnerability of banks that rely on wholesale funding, next to retail deposits. This underscores that liquidity risk management should identify and measure the full range of liquidity risks which banks could face.

Table 3 shows that in case of 33 banks, the decline of the liquidity buffer exceeds the threshold θ = 0.4 which triggers them to restore their liquidity buffer to the initial level (B_0). The reactions mitigate the first round effect of the scenario on the sector as a whole to around 3% on average (B_2 being 3% smaller than B_0). Figures A.9 and A.10 in the Annex indicate that larger banks with a more diversified funding structure tend to react relatively more than smaller banks, which relates to the stronger first round impact on the former group. According to the model (equation 6), the responses of the large banks potentially have a relatively strong impact on the markets. If threshold θ is doubled to 0.8 than only 13 banks would respond to the first round impact. Table 3 shows that this would limit the second round effects of the scenario, indicating the models' sensitivity to behavioural reactions. In particular the tail outcomes of the buffers are more favourable if fewer banks would react.

The second round of the scenario designed by assuming that the market illiquidity spills over into strained funding liquidity of the banks. Like in the recent credit crisis we assume that the difficulties to roll-over asset backed commercial paper (ABCP) imply an increased probability that off balance liquidity facilities are drawn. This looming liquidity need induces banks to hoard liquidity. Moreover, higher perceived counterparty risks induce banks to withdraw their promised credit lines. This contributes to dislocations in the unsecured interbank market. The increased counterparty risk among banks worsens their access to funding in the bond and commercial paper markets. Moreover, collective actions of banks (e.g. fire sales of assets) in response to the first round effect of the scenario could further disrupt credit and stock markets and raise margin calls. These second round effects ($w\_sim_{2,i}$) are simulated by further stressing the weights of the credit portfolios and margin requirements (on top of the first round effects) and by stressing the weights of the equity portfolios, unsecured interbank assets and liabilities, capital market liabilities and off balance liquidity committments. The reputation risk of the reacting banks translates into additional (idiosyncratic) stress on the weights ($w\_sim^*_{2,i}$) according to equation 7. Table 3 shows that the second round effects of the scenario have a larger impact than the first round effects; the banks additionally loose 26% of their initial liquidity buffers on average (including the effects of mitigation actions). A break down of the total second round effect indicates that more than half of the second round effects on the banks which react is caused by the idiosyncratic reputational effects. Several banks loose over 100% of their initial liquidity buffer which means that they become illiquid. Table 3 also shows the 5% and 1% tail outcomes of the final liquidity buffer for each bank and the probability of a liquidity shortfall (i.e. $B_3 < 0$). In the 5% (1%) tail the liquidity buffer declines by 68% (83%) on average. Out of the total sample, 33 banks have a probability larger than 0% to end up with a liquidity shortage. Figures A.11 and A.12 in the Annex indicate no significant correlation between the shortfall probability and size or funding diversification of banks, indicative of the systemic dimension of the second round effects, that affect all types of banks. This underscores that policy initiatives to enhance banks' liquidity buffers could contribute to prevent financial stability risks.

Table 3, Outcomes scenario simulations

EUR bn averages, unless stated otherwise

	Banking crisis	*Credit crisis*
	θ=0.4, s=1.5	θ=0.4, s=1.5
	horizon 1 mnt	horizon 1 mnt
Initial Buffer (B_0)	14.6	14.6
Buf. after 1st round (B_1)	13.5	12.6
# reactions, $\sum q$ (0,1)	30	33
Buf. after mitig. react. (B_2)	13.5	14.2
Buf. after 2nd round (B_3)	12.6	8.8
Buf. 5% tail (B_3)	10.8	4.7
Buf. 1% tail (B_3)	10.0	2.4
Prob. B_3<0 (wgt)	0.5%	2.5%
# banks Prob. B_3<0	25	33

4.3 Impact scenario length and market conditions

The recent liquidity crisis has been more prolonged than most banks assume in their liquidity stress-tests (FSF, 2008). These are typically based on a one to two months horizon. The same applies to liquidity frameworks of supervisors, like DNB's liquidity report. Our model allows for lengthening the stress horizon, by including the recognised cash inflows and outflows that fall due after one month as well in the simulations. In fact, the weights of assets and liabilities should also be changed according to the prolonged horizon, but they have not in the simulations as information of appropriate weights for longer horizons is lacking. This implies that the simulation outcomes probably underestimate the full impact of a prolonged horizon. To illustrate the sensitivity of the liquidity buffers for prolonged liquidity stress, we ran the credit crisis scenario at a 6 months horizon. Table 4 shows that lengthening the stress period has a substantial impact on the scenario outcomes, partly because with regard to the sample of Dutch banks the amount of liabilities falling due after one month exceeds the amount of cash inflows. At a 6 months horizon, the final average buffer turns out to be more than 100% lower compared to a 1 month horizon and the 1% tail outcome almost 150% lower. The latter indicates that a prolonged stress horizon has a relatively large impact on the extreme (tail) outcomes.

To illustrate the sensitivity of the model outcomes to changing market conditions, the credit crisis scenario has also been run with parameter value s = 2.0 in stead of s = 1.5. Table 4 shows that such an increase of market wide stress has a comparable impact as lengthening the scenario horizon. The relatively high probability of a liquidity shortfall indicates that the outcomes are quite sensitive to changing market conditions; raising the level of s has a relatively large impact on the extreme (tail) outcomes. This is conform the intuition that extreme market conditions can severely impact on the liquidity risk profile of banks.

Table 4, Parameter sensitivity credit crisis scenario

EUR bn averages, unless stated otherwise

	θ=0.4, s=1.5 horizon 1 mnt	θ=0.8, s=1.5 horizon 1 mnt	θ=0.4, s=1.5 horizon 6 mnt	θ=0.4, s=2.0 horizon 1 mnt
Initial Buffer (B_0)	14.6	14.6	14.6	14.6
Buf. after 1st round (B_1)	12.6	12.5	11.4	12.6
# reactions, $\sum q$ (0,1)	33	13	34	33
Buf. after mitig. react. (B_2)	14.2	13.5	13.9	14.2
Buf. after 2nd round (B_3)	8.8	9.8	5.5	4.4
Buf. 5% tail (B_3)	4.7	5.3	-0.1	-1.6
Buf. 1% tail (B_3)	2.4	3.7	-2.2	-4.0
Prob. B_3<0 (wgt)	2.5%	3.2%	19.9%	24.5%
# banks Prob. B_3<0	33	28	46	47

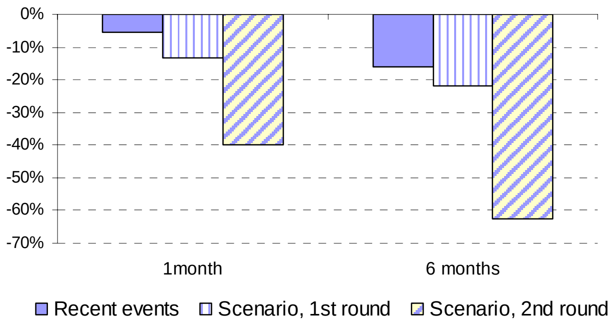
4.4 Back-test

As an anecdotal back-test, in Figure 5 the outcomes of the credit crisis scenario are compared to the actual change of the average liquidity buffer of the Dutch banks since July 2007, when the crisis began to unfold. The actual outcomes are rather close to the first round effects of the scenario (excluding mitigating actions), but are substantially smaller than the buffers modelled after the second round. This could indicate that the assumptions in Liquidity Stress-tester are inappropriate, for instance the assumptions that the weights in DNB's liquidity report resemble 0.1% tail events or that the threshold

θ for mitigating reactions is 0.4. Another explanation could be that some functional relationships in the model fail to reflect reality, for instance in case of the second round effects.

It could also be the case that the designed scenario is an imperfect replication of the recent crisis. This is amongst others characterised by a re-intermediation of assets by banks which are not able to fund those in the markets. Returning assets could be classified by banks as liquid items on their balance sheets which may distort the actual liquidity position of banks if market liquidity for such assets has dried up. In case of the Dutch banks this has not been a relevant factor since the off balance items are being consolidated in the balance sheet and hence recur in the DNB liquidity report. The difference between the actual and the model outcomes could also indicate that the extent of the recent market stress is not yet fully reflected in banks' balance sheets due to valuation issues. However, the most likely explanation of the differences between the simulation outcomes and actual developments is provided by the expanded liquidity operations of central banks in the money market, which have enabled banks to liquefy eligible collateral (against certain haircuts) for which the market had seized up. By doing so, central banks addressed a market failure, by breaking the loop between market and funding liquidity risk and preventing further market distress (Nikolaou, 2009). In terms of our model this implies that the value of certain collateral does not fully reflect the second round effects of the market turmoil (which have come to the fore in reduced liquidity and fallen mark-to-market values, in particular for structured credit securities which in some cases is eligible collateral for central bank borrowing). The simulation outcomes on the other hand, are dominated by the adverse second round effects on the liquidity buffers (in the scenario, the central bank facilities are only included implicitly and partially, i.e. for the banks which react through pledging collateral at the central bank).

Figure 5, Back-testing the scenario outcomes
Change of liquidity buffer since July 2007 (monthly data, average Dutch banks). Model parameters: θ=0.4; s=1.5



5. Conclusion

Liquidity Stress-Tester is an instrument to simulate the impact on banks of shocks to market and funding liquidity. It takes into account the important drivers of liquidity stress, i.e. on and off balance sheet contingencies, feedback effects induced by collective reactions of heterogeneous banks and idiosyncratic reputation effects. Contagion results from the effects of banks' reactions on prices and volumes in the markets where the banks are exposed to. The model contributes to understand the influence on liquidity risk of collective reactions by banks, the level of market stress and the length of the scenario horizon. These factors have been main drivers of the recent financial crisis. Liquidity Stress-Tester could be used by central banks to stress-test the liquidity risk at the level of the financial system. In the paper the model has been applied to Dutch banks, but it could also be applied to other countries' banking systems, provided that data for liquid assets and liabilities are available on an individual bank level. The parameters of the model (such as the weights and the threshold for reactions) can be tailored to a local banking sector according to the insights of the supervisor or central bank.

The model outcomes lend support to policy initiatives to enhance the liquidity buffers and liquidity risk management at banks, as recently proposed by the Basel Committee and the FSF (FSF, 2008). A sufficient level of liquidity buffers limits the idiosyncratic risks to a bank, by providing counterbalancing funding capacity to weather a liquidity crisis. Moreover, buffers are important to reduce the risk of collective reactions by banks and thereby to prevent the risk of amplifying effects and instability of the financial system as a whole. Admittedly, this should be considered in conjunction with the cost of holding higher liquidity buffers, also on the macro level of the financial system. To assess such equilibrium effects one would perhaps need a more stylised model of the financial system.

Holding liquidity buffers should be part of sound liquidity risk management, which identifies and measures the full range of liquidity risks, including the interaction between market and funding liquidity and potential feedbacks on banks' reputation related to signalling effects or flawed external communication. Furthermore, to fully grasp the liquidity risk of a bank, stress-tests should cover the group-wide liquidity exposures on a consolidated basis, including the risks of multi-currency exposures, complex instruments and off balance sheet contingencies. These factors are included in DNB's liquidity report which has proven to be useful for Dutch banks and the supervisor, particularly during the recent market turmoil. Based on the features of the liquidity report, Liquidity Stress-Tester provides a tool to evaluate the importance of the various risk factors for banks' liquidity positions at different scenarios.

References

Adrian and Shin (2007), Liquidity and Financial Cycles, 6th BIS Annual Conference, “Financial System and Macroeconomic Resilience”, June 2007, Brunnen.

Adrian and Shin (2008), Liquidity and financial contagion, in Banque de France, Financial Stability Review, No. 11.

Allen and Gale (2000), Financial Contagion, Journal of Political Economy, Vol. 108, No. 1, p. 1-33.

Alessandri, Gai, Kapadia, Mora and Puhr (2008), A Framework for Quantifying Systemic Stability, conference paper.

Aspachs, Goodhart, Segoviano, Tsomocos and Zicchino (2006), Searching for a Metric for Financial Stability, Special Paper, Oxford Financial Research Center, No 167.

Banque de France (2008), Financial Stability Review, special issue Liquidity, No. 11, February 2008.

Basel Committee on Banking Supervision, BCBS (2008), Liquidity Risk: Management and Supervisory Challenges.

Bech, Chapmanz and Garratt (2007), Which Bank is the Central Bank?: An Application of Markov Theory to the Canadian Large Value Transfer System, Bank of Canada conference paper.

Boss, Breuer, Elsinger, Jandacka, Krenn, Lehar, Puhr and Summer (2006), Systemic Risk Monitor: A Model for Systemic Risk Analysis and Stress Testing of Banking Systems, OeNB, Internal technical report.

Brunnermeier and Pederssen (2007), Market Liquidity and Funding Liquidity, NBER Working Paper No. W12939.

Cifuentes, Ferrucci and Shin (2005), Liquidity risk and contagion, Journal of the European Economic Association, Vol. 3, 556-66.

Diamond and Rajan (2005), Liquidity Shortages and Banking Crises, The Journal of Finance, Vol. LX, No. 2.

DNB (2003), Credit System Supervision Manual, articles 44 – 47, 2.3 Liquidity Risk (www.dnb.nl)

Financial Services Authority, FSA (2007), Review of the liquidity requirements for banks and building societies, Discussion Paper 07/07.

Financial Stability Forum, FSF (2008), Report of the Financial Stability Forum on Enhancing Market and Institutional Resilience.

Freixas, Parigi and Rochet (2000), Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank, Journal of Money, Credit and Banking, 32, p. 611- 638.

Goetz von Peter (2004), Asset prices and banking distress: a macroeconomic approach, BIS Working Papers No. 167.

Goodhart, Sunirand and Tsomocos (2006), A model to analyse financial fragility, Economic Theory, Springer, Vol. 27(1), p. 107-142, 01.

IMF (2008), Global Financial Stability Report, April 2008.

Ledruth (2007), Simulating retaliation in payment systems: Can banks control their exposure to a failing participant?, DNB Working Paper No. 133.

Leinonen ed. (2005), Liquidity, risks and speed in payment and settlement systems – a simulation approach, Bank of Finland Studies.

Nier, Yang, Yorulmazer and Alentorn (2008), Network models and financial stability, Bank of England, Working Paper No. 346.

Nikolaou (2009), Liquidity (risk) concepts, definitions and interactions, ECB Working paper, No. 1008.

Standard & Poor's (2007), Liquidity Risk Analysis: Canadian Banks.

Upper (2006), Contagion Due to Interbank Exposures: What Do We Know, Why Do We Know It and What Should We Know?, Discussion Paper, Bank for International Settlements.

ANNEX

Table A (Credit System Supervision Manual, articles 44 – 47, 2.3 Liquidity Risk, www.dnb.nl)

LIQUIDITY VALUES OF ASSETS AND LIABILITIES

For the liquidity test for the full month, a distinction is made between non-scheduled items and scheduled items. In contrast to non-scheduled items, scheduled items are included on the basis of their possible or probable due dates. For the liquidity test for the first week, scheduled items are only included if they are explicitly taken into account in day-to-day liquidity management (treasury operations). In the following table, scheduled items are indicated by the letter M.

		ASSETS	M	WEEK	MONTH
1.		Banknotes/coins		100	100
2.		Receivables from central banks (including ECB)			
	1	Demand deposits		100	100
	2	Amounts receivable	M	100	100
	3	Receivables in respect of reverse repos	M	100	100
	4	Receivables in the form of securities or tier 2 eligible assets	M	d*	d*
3.		Collection documents			
	1	Available on demand		100	100
	2	Receivable	M	100	100
4.		Readily marketable debt instruments/ECB eligible assets			
4.0		*Issued by public authorities and central banks*			
	1	ECB tier 1 and tier 2 eligible assets		95**	95**
	2	ECB tier 2 eligible assets, deposited		85**	85**
	3	ECB tier 2 eligible assets, not deposited		85	85
	4	Other readily marketable debt instruments, Zone A		95	95
	5	Other readily marketable debt instruments, Zone B		70	70
4.1		*Issued by credit institutions*			
	1	ECB tier 1 eligible assets		90**	90**
	2	ECB tier 2 eligible assets, deposited		80**	80**
	3	Other debt instruments qualifying under the CAD		90	90
	4	Other liquid debt instruments		70	70
4.2		*Issued by other institutions*			
	1	ECB tier 1 eligible assets		90**	90**
	2	ECB tier 2 eligible assets, deposited		80**	80**
	3	Other debt instruments qualifying under the CAD		90	90
	4	Other liquid debt instruments		70	70
5.		Amounts receivable			
5.0		*Branches and banking subsidiaries not included in the report*			
	1	Demand deposits		50	100
	2	Amounts receivable in respect of securities transactions	M)	100	100

	3	Other amounts receivable	M	100	90
5.1		*Other credit institutions*			
	1	Demand deposits		50	100
	2	Amounts receivable in respect of securities transactions	M)	100	100
	3	Other amounts receivable	M	100	90
5.2		*Public authorities*			
	1	Demand deposits		50	100
	2	Amounts receivable in respect of securities transactions	M)	100	100
	3	Other amounts receivable	M	100	90
5.3		*Other professional money market players*			
	1	Demand deposits		50	100
	2	Amounts receivable in respect of securities transactions	M)	100	100
	3	Other amounts receivable	M	100	90
5.4		*Other counterparties*			
	1	Demand deposits		0	0
	2	Amounts receivable in respect of securities transactions	M)	100	90
	3	Other amounts receivable, inlcuding premature redemptions	M	50	40
6.		Receivables in respect of repo and reverse repo transactions			
6.0		*Reverse repo transactions (other than with central banks)*			
	1	Receivables in respect of bonds	M	100	100
	2	Receivables in respect of shares	M	100	100
6.1		*Repo transactions (other than with central banks)*			
	1	Receivables in the form of bonds	M	90/d*/**	90/d*/**
	2	Receivables in the form of shares	M	70	70
6.2		*Securities lending/borrowing transactions*			
	1	Securities stock on account of securities lending/borrrowing transactions		100	100
	2	Securities receivable on account of securities lending/borrowing transactions	M	100	100
7.		Other securities and gold			
	1	Other liquid shares		70	70
	2	Unmarketable shares		0	0
	3	Unmarketable bonds	M	100	100
	4	Gold		90	90
8.		Official standby facilities			
	1	Official standby facilities received		100	100
9.		Receivables in respect of derivatives	M	***	***
10.		Total			

		LIABILITIES	M	WEEK	MONTH
11.		Moneys borrowed from central banks			
	1	Overdrafts (payable within one week)		100	100
	2	Other amounts owed	M	100	100
12.		Debt instruments issued by the bank itself			
	1	Issued debt securities	M	100	100
	2	Subordinated liabilities	M	100	100
13.		Deposits and fixed term loans			
13.0		*Branches and banking subsidiaries not included in the report*			
	1	Amounts owed in respect of securities transactions	M)	100	100
	2	Deposits and other funding – fixed maturity	M	100	90
13.1		*Other credit institutions*			
	1	Amounts owed in respect of securities transactions	M)	100	100
	2	Deposits and other funding – fixed maturity	M	100	90
13.2		*Other professional money market players*			
	1	Amounts owed in respect of securities transactions	M)	100	100
	2	Deposits and other funding – fixed maturity – plus interest payable	M	100	90
13.3		*Other counterparties*			
	1	Amounts owed in respect of securities transactions	M)	100	100
	2	Deposits and other funding – fixed maturity – plus interest payable	M	50	40
	3	Fixed-term savings deposits	M	20	20
14		Liabilities in respect of repo and reverse repo transactions			
14.0		*Repo transactions other than with central banks*			
	1	Amounts owed in respect of bonds	M	100	100
	2	Amounts owed in respect of shares	M	100	100
14.1		*Reverse repo transactions other than with central banks*			
	1	Amounts owed in the form of bonds	M	100	100
	2	Amounts owed in the form of shares	M	100	100
14.2		*Securities lending/borrowing transactions*			
	1	Negative securities stock on account of securities lending/borrowing transactions		100	100
	2	Securities to be delivered on account of securities lending/borrowing transactions	M	100	100
15.		Credit balances and other moneys borrowed with an indefinite effective term			
15.0		*Branches and banking subsidiaries not included in the report*			
	1	Current account balances and other demand deposits		50	100
15.1		*Other credit institutions*			
	1	Balances on vostro accounts of banks		50	50
	2	Other demand deposits		50	100
15.2		*Other professional money market players*			

	1	Demand deposits		50	100
		LIABILITIES (continued)	M	WEEK	MONTH
15.3		*Savings accounts*			
	1	Savings accounts without a fixed term		2.5	10
15.4		*Other*			
	1	Demand deposits and other liabilities		5	20
	2	Other amounts due and to be accounted for, including the balance of forward transactions and amounts due in respect of social and provident funds		5	20
16.		Official standby facilities			
	1	Official standby facilities granted		100	100
17.		Liabilities in respect of derivatives			
	1	Known liabilities in respect of derivatives	M	***	***
	2	Unknown liabilities in respect of derivatives		***	***
18.		Other contingent liabilities and irrevocable credit facilities			
	1	Unused irrevocable credit facilities, including underwriting of issues		2.5	10
	2	Bills accepted	M	100	100
	3	Credit-substitute guarantees		2.5	10
	4	Non-credit-substitute guarantees		1.25	5
	5	Other off-balance-sheet liabilities		1.25	5
20.		Total			

M = Scheduled item.

M) = Settlement due within one week or open-ended, including first week or as scheduled.

* = Less applicable discount.

** = Either at stated percentage or at percentages applicable for ECB/ESCB collateral purposes.

*** = Calculated amount for the period concerned.

90/d*/** = 90% OR: less applicable discount (provided the method is consistently applied).

Table B, Stylised balance sheet bank Y (base line)

Assets		*weights* w_1	w_2	w_2*	**Liabilities**		*run-off schedule* 1m	3m	6m	9m	12m	*weights* w_1	w_2	w_2*
asset_1	30	10	16	19	liab_1 (cal)	5	5	3	2	0.5	0.5	100	100	100
asset_2	15	30	47	57	liab_2 (non-cal)	30						5	8	10
					equity	4								
	45					45								

Initial liquidity buffer:

B_0= **45.0** (30 + 15)

Buffer after 1st round effects:

B_1= **31.0** (30*(1-0.1) + 15*(1-0.3)) - (5*1 + 30*.05)

Amount of mitigating reactions:

RI_{wg}= **6.8** (45-31)*30/(45+45)*(1-0.1) + (45-31)*15/(45+45)*(1-0.3) + (45-31)*5/(45+45)*1 + (45-31)*30/(45+45)*(0.05)

Buffer after mitigating reactions:

B_2= **37.8** (31 + 6.8 if reaction, 31 if no reaction)

Buffer after 2nd round effects:

B_3 **28.5** if bank Y reacts: 37.8 - (30+(45-31)*30/(45+45)*(0.19 - 0.1) - (15+(45-31)*15/(45+45)*(0.57 - 0.3) -(5+(45-31)*5/(45+45)*(1-1) - (30+(45-31)*30/(45+45)*(0.1 - 0.05)

Assumptions:

a) one bank model

b) 1st round effect hits all balance sheet items

c) bank Y reacts with all instruments at its disposal

Figures A1..A6, Impact banking crisis scenario

Figure A.1 Bank size & 1st round impact
Impact (E_1 / B_o), share in total sectors' assets (x-axis)

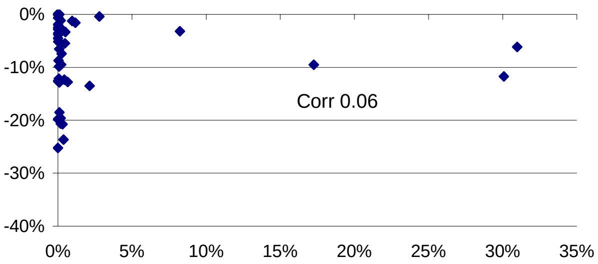


Figure A.2 Funding diversification & 1st round impact
Impact (E_1 / B_o), kurtosis of funding structure (x-axis)

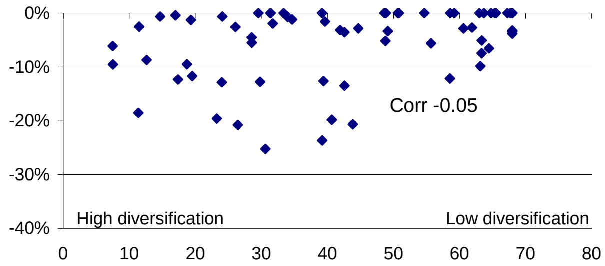
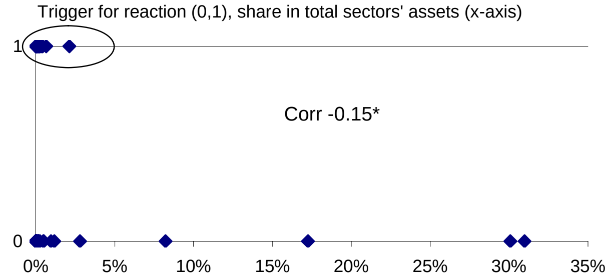
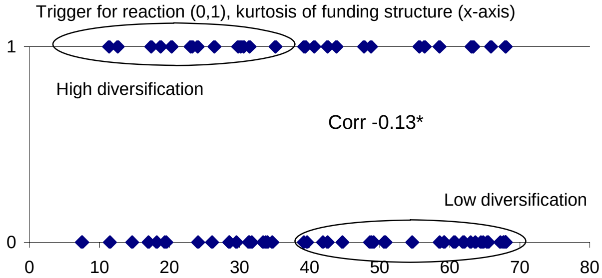


Figure A.3 Bank size & reaction
Trigger for reaction (0,1), share in total sectors' assets (x-axis)



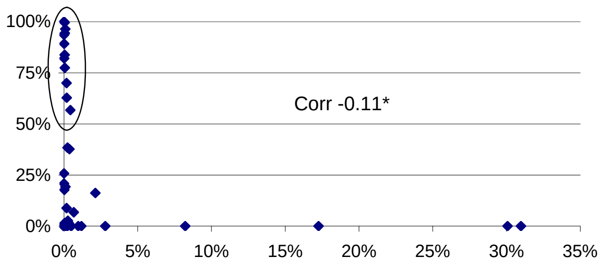
* significant at 10% confidence level

Figure A.4 Funding diversification & reaction
Trigger for reaction (0,1), kurtosis of funding structure (x-axis)



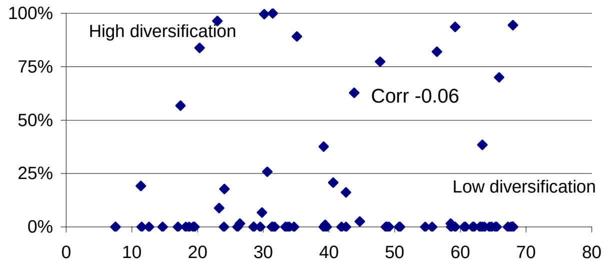
* significant at 10% confidence level

Figure A.5 Bank size & shortfall probability
Probability B_3<0, share in total sectors' assets (x-axis)



* significant at 10% confidence level

Figure A.6 Funding diversification & shortfall probability
Probability B_3<0, kurtosis of funding structure (x-axis)



Figures A7..A12, Impact credit crisis scenario

Figure A.7 Bank size & 1st round impact
Impact (E_1 / B_o), share in total sectors' assets (x-axis)

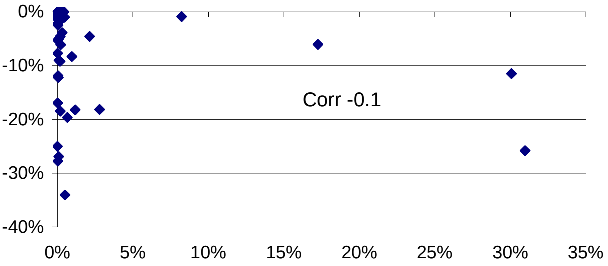
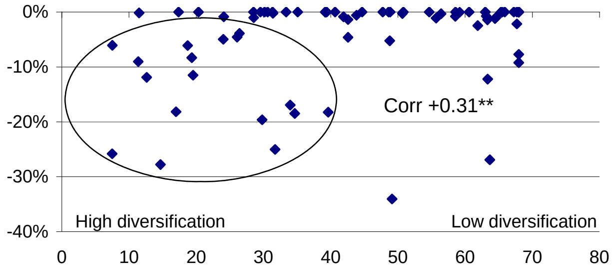
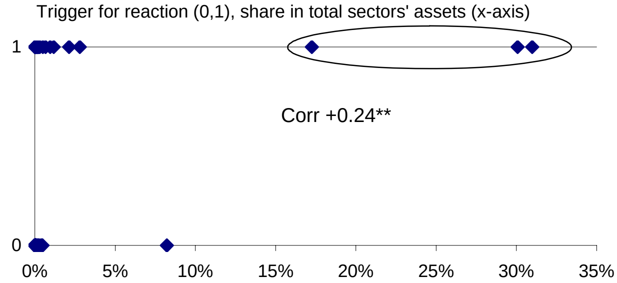


Figure A.8 Funding diversification & 1st round impact
Impact (E_1 / B_o), kurtosis of funding structure (x-axis)



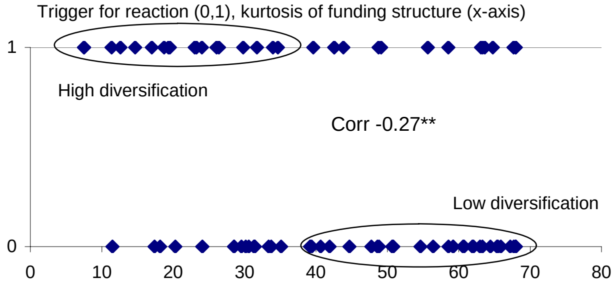
** significant at 5% confidence level

Figure A.9 Bank size & reaction
Trigger for reaction (0,1), share in total sectors' assets (x-axis)



** significant at 5% confidence level

Figure A.10 Funding diversification & reaction
Trigger for reaction (0,1), kurtosis of funding structure (x-axis)



** significant at 5% confidence level

Figure A.11 Bank size & shortfall probability
Probability B_3<0, share in total sectors' assets (x-axis)

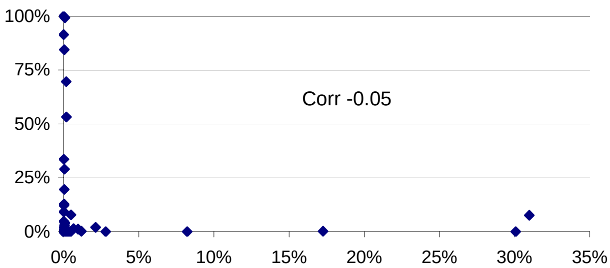


Figure A.12 Funding diversification & shortfall probability
Probability B_3<0, kurtosis of funding structure (x-axis)