

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

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

Jan Willem van den End*

* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

Working Paper No. 175/2008

May 2008

De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

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

Jan Willem van den End*

May 2008

Abstract

This paper presents a macro stress-testing model for market and funding liquidity risks of banks, which have been main drivers of the recent financial crisis. The model takes into account the first and second round (feedback) effects of shocks, induced by behavioural reactions of heterogeneous banks, and idiosyncratic reputation effects. The impact on liquidity risk is simulated by a Monte Carlo approach. This generates distributions of liquidity buffers for each scenario round, including the probability of a liquidity shortfall. An application to Dutch banks illustrates that the second round effects 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

* Jan Willem van den End (w.a.van.den.end@dnb.nl) is in the Financial Stability Division of De Nederlandsche Bank (DNB). The views expressed in this paper are those of the author and do not necessarily reflect those of DNB. The author would like to thank Mostafa Tabbæ for excellent statistical support and colleagues of the Financial Stability Division and the Economics and Research division for valuable comments on earlier versions.

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 macro 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. Section 4 presents model simulations for Dutch banks as an illustration. It also provides a parameter sensitivity analysis and a 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 plays a key role through the change of banks' liquidity supply 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 has value added to the existing studies as it covers both market and funding liquidity risk of banks in a macro stress-testing framework. It takes 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 the banks are exposed to. Possible market stress caused by other developments is included in the model as an exogenous variable.

3. Model

3.1 Framework

In stylised form the Liquidity Stress-Tester model can be represented by Figure 1. Banks' liquidity profiles 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 (including tail outcomes and probabilities of a liquidity shortfall) by bank. 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).

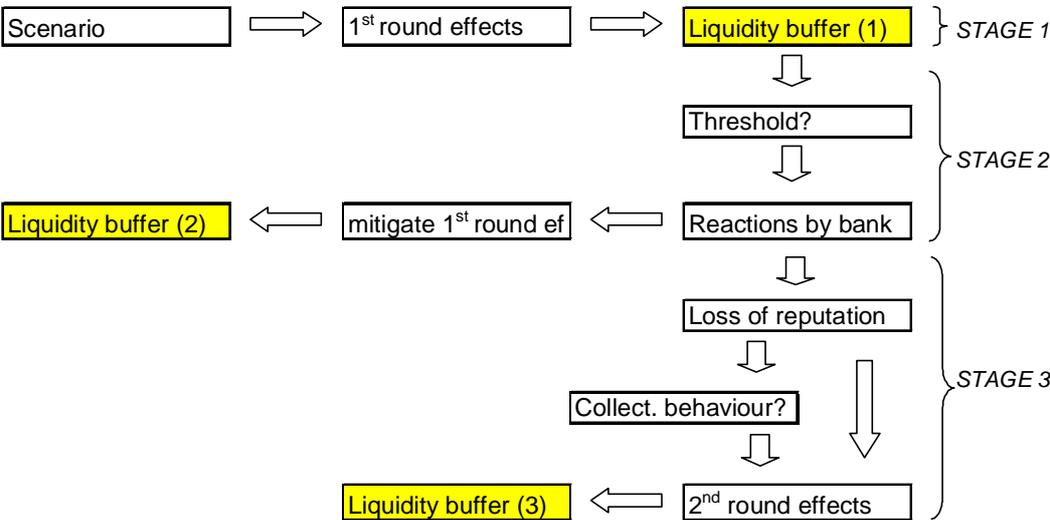
In the first stage, the first round effects of a scenario on banks' liquidity buffers are simulated (first line of flow chart in Figure 1). This is conducted through Monte Carlo simulations of market and liquidity risk events, which are combined in a multi-factor scenario. This is uniformly applied to individual banks. Both the first and second rounds of a scenario are designed as consistent sets of

shocks to banks' liquid asset and liability items (i). The shocks are reflected in stressed weights of the items (w_i), with w_i being the haircut in case of liquid assets and withdrawal rate in case of liabilities. The weights translate the reduced liquidity value of assets and the drying up of funding by various causes (e.g. a rise of banks' credit spreads leading to reduced wholesale refinancing or a run on retail deposits) into one measure which indicates the difference with a going concern situation. The model is flexible to choose any combination of shocks, being modelled as stressed values of liquid assets and liabilities. For instance, a credit market scenario can be designed by assuming shocks to tradable credit portfolios, collateral values and margin calls on derivative exposures as first round effects.

The second stage simulates the mitigating measures by banks in response to the initial shock. The design of the second round of the scenario determines the type of measures (e.g. in which markets banks react). The responses are assumed to be triggered if the decline of the liquidity buffer breaches a predefined threshold (second line of flow chart). Besides the mitigating effect on the buffers, the reaction to the scenario could also have negative repercussions for the reacting bank. This relates to reputational risk, since a bank might be perceived to be in trouble by conducting measures to restore its liquidity buffer (signalling effect). Next to the idiosyncratic risk, collective reactions by banks could lead to wider disturbing effects on financial markets (systemic risk).

Both these possible second round effects determine the third stage in the model (third line of flow chart). Liquidity Stress-Tester takes into account that systemic risk is larger if i) more banks would react, ii) reactions would be more similar and iii) the reacting bank is larger. For instance in the case of a credit market scenario, the collective actions of banks (e.g. through withdrawal of credit lines, fire sales of assets etc.) might give rise to an increase of margin calls, dislocations in the unsecured interbank markets and falling stock prices. Both the possible loss of reputation and the wider effects on markets have an impact on the liquidity buffers of the banks through additional haircuts on liquid assets and withdrawals of liquid liabilities.

Figure 1, flow chart of Liquidity Stress-Tester



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 events² ($w_i \approx 3 \times \sigma$). The scenario impact of the first round effect on an item i is determined by simulated weights ($w_{sim,i}$). These are based on Monte Carlo simulations by taking random draws from a normal distribution that is scaled by ($w_i / 3$) and transformed to a log-normal distribution³, so that $w_{sim,i} \sim \text{Log-N}(\mu, \sigma^2)$. 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

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 The log normal distribution is derived by $\text{Exp}(N(0,1) * (w_i / 3))$, based the fact that if $X \sim N(\mu, \sigma^2)$ is a normal distribution then $\text{Exp}(X) \sim \text{Log-N}(\mu, \sigma^2)$.

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 the simulated weights in our model. As an upper bound, the weights are conditioned by $w_{sim_{l,i}} \leq 100$, since haircuts and withdrawal rates can not exceed 100%. The liquidity buffer in the baseline situation (normal market conditions), B_0 , is

$$B_0^b = \sum_{i=1}^{nc} I_{non-cal,i}^b \quad (1)$$

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 $1 \dots nc$). 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_l) of the scenario is determined by,

$$E_l^b = \sum_i I_i^b \times w_{sim_{l,i}} \quad (2)$$

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_l , is,

$$B_l^b = B_0^b - E_l^b \quad (3)$$

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 relative decline of original liquidity buffer (as reflected in the simulated buffers) that exceeds a threshold θ . Hence, trigger q (0, 1) is determined by $\frac{E_l^b}{B_0^b} > \theta$.

The value of θ can be underpinned by analysing the reaction function of banks. This is approximated by correlating the value change of balance sheet items to the decline of the liquidity buffer one month lagged, for each bank (based on data for 82 Dutch banks, 80 monthly periods, covering 2001-4 to 2007-12). The value change of balance sheet items is assumed to reflect banks' responses to the buffer

decline. The lag controls for the influence of possible endogeneity in the relationship between the buffers and the balance sheet items.⁴

$$\text{Correl} \left(\frac{B_{t=0}^b - B_{t=-1}^b}{B_{t=-1}^b}, \frac{I_{i,t=1}^b - I_{i,t=0}^b}{I_{i,t=0}^b} \right), \text{ conditioned by } \frac{B_{t=0}^b - B_{t=-1}^b}{B_{t=-1}^b} < 0$$

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.

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 determined by the second round of the 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 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

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.

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 is 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 ,

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

Since $B_1 \leq B_2$, 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,

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

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 ($\sum_b RI_i^b$). In the case of deep and liquid 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,

$$w_sim_{2,i} = w_sim_{1,i} \times (\sum_b q \wedge (1 + \sum_b RI_i^b / \sum_i \sum_b RI_i^b) \times s) / \sum_b q \quad (6)$$

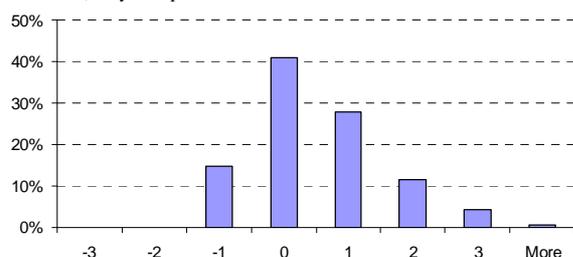
⁶ The model does not specify the conditions (e.g. credit spreads) at which funding is attracted.

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 et 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 level of market stress.

s is 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

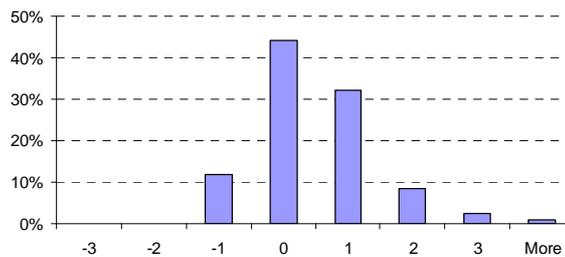
Normalised value of Moodys Baa average credit spreads on corporate bonds, daily data period 1986-2007



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

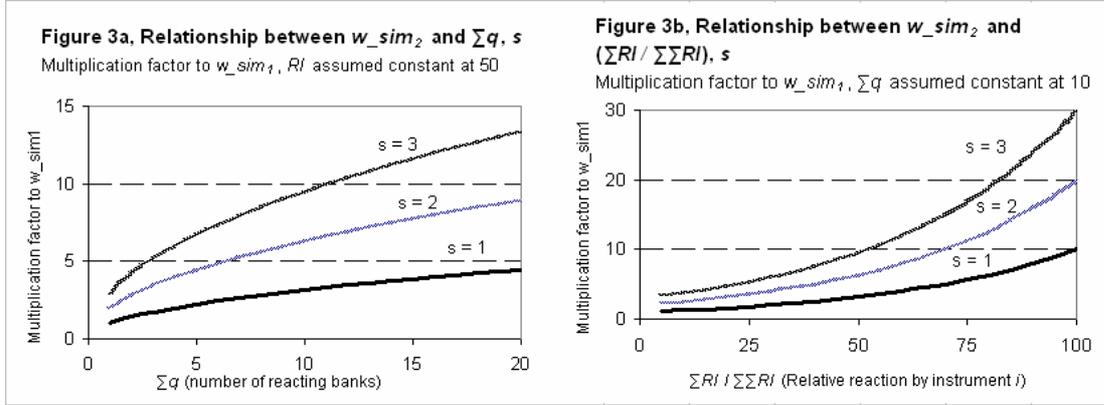


Source of VIX: Chicago Board Option Exchange

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).

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.

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.



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,

$$w_{sim_{2,i}}^* = w_{sim_{2,i}} \times \sqrt{s} \quad (7)$$

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

$$E_2^b = \sum_i ((I_i^b + RI_i^b) \times (w_{sim_{2,i}} - w_{sim_{1,i}})) \quad (8)$$

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,

$$B_3^b = B_2^b - E_2^b \quad (9)$$

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 4.1). If $s = 1$ (the downside restriction for s), then the mitigating reaction of a bank will not be counteracted by adverse reputational effects and will improve a banks' liquidity position by definition.

3.6 Impact different scenario rounds

In the model, each round of a scenario has its typical effect on the distribution of buffer outcomes. Simulations 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 peaking of the shape (Figure 4b)⁹. If a bank does not react because $\frac{E_i}{B_0} < \theta$, 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. 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).

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

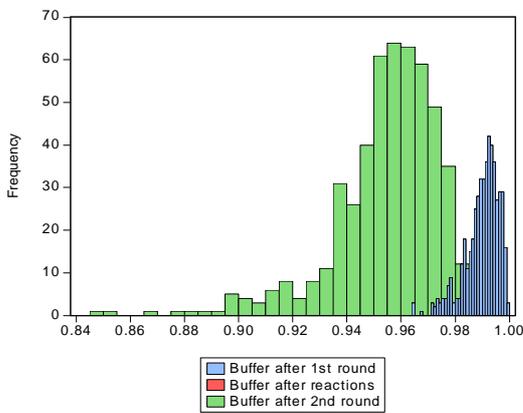
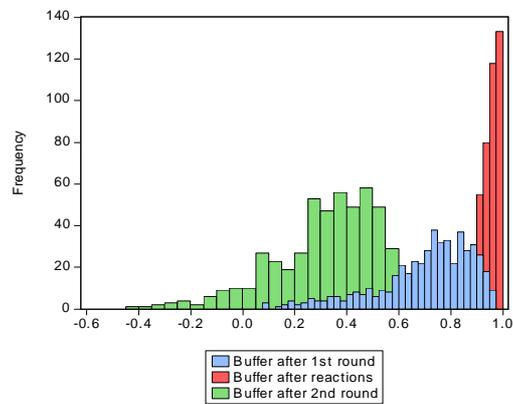


Figure 4b, Distribution of buffers after each scenario round
EUR bn, for bank AU as illustration, buffers normalised by B_0 ($\theta=0.4$, $s=1.5$)



4. Results

4.1. Credit crisis scenario

This section describes model outcomes by simulating the recent credit market crisis. The model is run with July 2007 data of all 82 banks in the Netherlands (including subsidiaries of foreign banks). The outcomes are based on 500 Monte Carlo simulations. In first instance we assume $\theta = 0.4$ (the critical threshold determined in section 3.4), $s = 1.5$ (the middle of the range determined in section 3.5¹⁰) 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 4.2). 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.

⁹ The parameters of these simulations are equal to those applied in section 4.1.

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.

The first round effect of the scenario 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 $w_{sim_{1,i}}$). These weights determine the first round effect (E_1) according to equation 2 and the liquidity buffer (B_1) according to equation 3. Table B in the Annex shows the outcomes for all 82 banks. It indicates that most banks would be affected by the scenario (i.e. $B_1^b < B_0^b$).¹¹ 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. 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.2 in Annex, Figure A.1 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 2 shows that in case of 33 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).¹² 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.3 and A.4 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

¹¹ The fact that some banks have a liquidity buffer of 0.0 in the Table is in most cases due to the rounding of very small numbers. Besides, there are some small banks that do not have a liquidity buffer according to the definition in the model, either because they do not report this to DNB or because they are branches of foreign banks which rely on their mother bank for liquidity.

¹² The Table reports the averages of the simulated buffers, whereas the reactions are triggered by extreme downward changes in the simulated sample of buffers.

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 commitments. The reputation risk of the reacting banks 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 B in the Annex shows the outcomes for all 82 banks. It appears that the second round effects of the scenario have a larger impact than the first round effects; the banks additionally lose 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 lose over 100% of their initial liquidity buffer which means that they become illiquid. Table 2 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. $B_3 < 0$). 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 68% (83%) on average. Out of the total sample, 33 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 2.5%. The latter is an indicator of the liquidity risk of the financial system as a whole. Figures A.5 and A.6 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.

4.2 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 Liquidity Stress-Tester at a 6 months horizon. Table 2 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, Liquidity Stress-Tester has also been run with parameter value $s = 2.0$ in stead of $s = 1.5$. Table 2 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 2, Parameter sensitivity				
EUR bn averages, unless stated otherwise				
	$\theta=0.4, s=1.5$ horizon 1 mnt	$\theta=0.8, s=1.5$ horizon 1 mnt	$\theta=0.4, s=1.5$ horizon 6 mnt	$\theta=0.4, s=2.0$ horizon 1 mnt
Initial Buffer (B_0)	14.6	14.6	14.6	14.6
Buf. after 1 st round (B_1)	12.6	12.5	11.4	12.6
# reactions, $\sum q_i(0,1)$	33	13	34	33
Buf. after mitig. react. (B_2)	14.2	13.5	13.9	14.2
Buf. after 2 nd 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

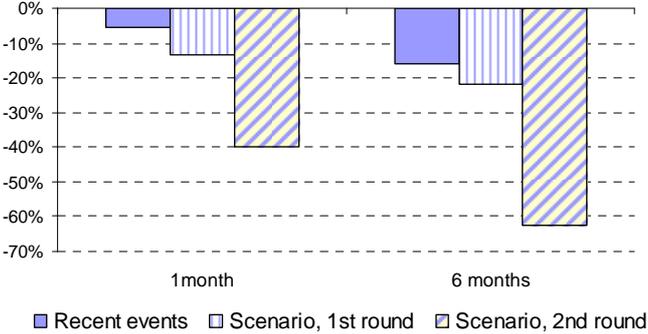
4.3 Back-test

As a simple back-test, in Figure 5 the scenario outcomes are compared to the actual change of the average liquidity buffer of the Dutch banks since July 2007, when the credit 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 liquidity injections 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, which by definition 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: $\theta=0.4$; $s=1.5$



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 instability of the financial system as a whole. 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 Pühr (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, Chapman 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, Pühr and Summer (2006), Systemic Risk Monitor: A Model for Systemic Risk Analysis and Stress Testing of Banking Systems, OeNB, Internal technical report.
- Brunnermeier and Pedersen (2006), 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.
- Ledruith (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.
- 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	<i>Issued by public authorities and central banks</i>			
	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	<i>Issued by credit institutions</i>			
	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	<i>Issued by other institutions</i>			
	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	<i>Branches and banking subsidiaries not included in the report</i>			
	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	<i>Other credit institutions</i>			
	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	<i>Public authorities</i>			
	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	<i>Other professional money market players</i>			
	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	<i>Other counterparties</i>			
	1 Demand deposits		0	0
	2 Amounts receivable in respect of securities transactions	M)	100	90
	3 Other amounts receivable, including premature redemptions	M	50	40
6.	Receivables in respect of repo and reverse repo transactions			

6.0		<i>Reverse repo transactions (other than with central banks)</i>			
	1	Receivables in respect of bonds	M	100	100
	2	Receivables in respect of shares	M	100	100
6.1		<i>Repo transactions (other than with central banks)</i>			
	1	Receivables in the form of bonds	M	90/d*/**	90/d*/**
	2	Receivables in the form of shares	M	70	70
6.2		<i>Securities lending/borrowing transactions</i>			
	1	Securities stock on account of securities lending/borrowing 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		<i>Branches and banking subsidiaries not included in the report</i>			
	1	Amounts owed in respect of securities transactions	M)	100	100
	2	Deposits and other funding – fixed maturity	M	100	90
13.1		<i>Other credit institutions</i>			
	1	Amounts owed in respect of securities transactions	M)	100	100
	2	Deposits and other funding – fixed maturity	M	100	90
13.2		<i>Other professional money market players</i>			
	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		<i>Other counterparties</i>			
	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		<i>Repo transactions other than with central banks</i>			
	1	Amounts owed in respect of bonds	M	100	100
	2	Amounts owed in respect of shares	M	100	100
14.1		<i>Reverse repo transactions other than with central banks</i>			
	1	Amounts owed in the form of bonds	M	100	100
	2	Amounts owed in the form of shares	M	100	100
14.2		<i>Securities lending/borrowing transactions</i>			
	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		<i>Branches and banking subsidiaries not included in the report</i>			
	1	Current account balances and other demand deposits		50	100
15.1		<i>Other credit institutions</i>			
	1	Balances on vostro accounts of banks		50	50

	2	Other demand deposits		50	100
15.2		<i>Other professional money market players</i>			
	1	Demand deposits		50	100
		LIABILITIES (continued)	M	WEEK	MONTH
15.3		<i>Savings accounts</i>			
	1	Savings accounts without a fixed term		2.5	10
15.4		<i>Other</i>			
	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, Output of simulation credit crisis scenario								
EUR bn averages, unless stated otherwise ($\theta = 0.4$; $s = 1.5$, horizon 1mnt, $n = 500$ simulations)								
Bank	Initial liquidity buffer	Buffer after 1st round	Reaction (0,1)	Buffer after reactions	Buffer after 2nd round	Buffer 5% tail	Buffer 1% tail	Probability buffer < 0
a	0.0	0.0	0	0.0	0.0	0.0	0.0	0%
b	0.0	0.0	0	0.0	0.0	0.0	0.0	1%
c	1.1	1.1	0	1.1	1.0	0.8	0.7	0%
d	0.1	0.0	1	0.1	-0.1	-0.5	-0.7	99%
e	4.6	4.2	1	4.6	4.2	2.3	1.5	0%
f	0.2	0.2	1	0.2	0.2	0.2	0.0	1%
g	0.3	0.3	1	0.3	0.3	0.1	0.0	0%
h	1.2	1.2	0	1.2	1.2	1.2	1.2	0%
i	0.6	0.6	1	0.6	0.5	0.4	0.3	0%
j	0.2	0.2	0	0.2	0.2	0.2	0.1	0%
k	0.2	0.2	1	0.2	0.2	0.1	0.1	0%
l	0.3	0.3	0	0.3	0.3	0.3	0.2	0%
m	0.5	0.5	0	0.5	0.4	0.2	0.1	0%
n	0.5	0.5	1	0.5	0.0	-0.5	-0.7	53%
o	0.0	0.0	1	0.0	0.0	0.0	0.0	12%
p	42.7	34.9	1	41.4	33.7	16.7	11.6	0%
q	0.5	0.4	1	0.5	0.4	0.0	-0.1	4%
r	3.4	3.4	0	3.4	2.2	1.1	0.4	0%
s	4.3	3.5	1	4.2	2.8	2.0	1.7	0%
t	0.0	0.0	0	0.0	0.0	0.0	0.0	0%
u	0.1	0.1	0	0.1	0.0	-0.1	-0.3	20%
v	2.1	2.0	1	2.1	1.6	1.2	0.7	0%
w	0.7	0.6	1	0.7	0.6	0.5	0.3	0%
x	0.3	0.3	0	0.3	0.3	0.3	0.2	0%
y	0.9	0.9	0	0.9	0.8	0.8	0.8	0%
z	0.3	0.3	0	0.3	0.3	0.2	0.2	0%
aa	1.3	1.3	1	1.3	1.1	0.8	0.4	0%
ab	1.1	1.1	0	1.1	1.0	0.8	0.7	0%
ac	0.0	0.0	0	0.0	0.0	0.0	0.0	9%
ad	0.0	0.0	0	0.0	0.0	0.0	-0.1	13%
ae	0.1	0.1	0	0.1	0.1	0.1	0.1	0%
af	0.1	0.1	0	0.1	0.0	0.0	0.0	0%
ag	0.9	0.1	1	0.7	-0.4	-1.3	-1.5	70%
ah	176.7	175.1	0	175.1	169.3	161.5	156.2	0%
ai	0.7	0.7	1	0.7	0.6	0.4	0.2	0%
aj	0.5	0.5	1	0.5	0.3	0.1	0.0	0%
ak	0.0	0.0	0	0.0	0.0	0.0	0.0	0%
al	0.0	0.0	0	0.0	0.0	0.0	0.0	0%
am	0.0	0.0	0	0.0	0.0	0.0	0.0	100%
an	0.0	0.0	0	0.0	0.0	0.0	0.0	0%
ao	0.3	0.3	1	0.3	0.2	0.2	0.1	1%
ap	0.1	0.1	0	0.1	0.1	0.0	0.0	0%
aq	0.0	0.0	0	0.0	0.0	0.0	0.0	0%
ar	0.2	0.1	1	0.2	0.1	0.0	0.0	5%
as	0.4	0.3	1	0.4	0.2	0.1	0.0	0%
at	357.3	316.2	1	349.4	221.2	132.3	71.4	0%
au	362.5	268.9	1	344.4	129.0	-22.4	-98.2	8%
av	0.0	0.0	0	0.0	0.0	-0.1	-0.2	84%
aw	0.0	0.0	0	0.0	0.0	0.0	0.0	0%
ax	2.8	2.8	0	2.8	2.5	2.1	1.6	0%
ay	0.1	0.1	0	0.1	0.1	0.1	0.0	0%
az	0.2	0.2	0	0.2	0.1	0.0	0.0	2%
ba	0.4	0.4	1	0.4	0.3	0.2	-0.1	1%
bb	0.1	0.0	0	0.0	0.0	0.0	0.0	0%
bc	0.0	0.0	0	0.0	0.0	-0.2	-0.4	29%
bd	1.9	1.2	1	1.8	0.7	-0.3	-0.7	8%
be	4.3	4.3	0	4.3	3.4	2.4	2.1	0%
bf	0.0	0.0	0	0.0	0.0	0.0	0.0	0%
bg	0.0	0.0	0	0.0	0.0	0.0	0.0	0%
bh	0.0	0.0	0	0.0	0.0	0.0	0.0	0%
bi	0.2	0.2	0	0.2	0.1	0.0	-0.1	3%
bj	0.2	0.2	0	0.2	0.2	0.2	0.2	0%
bk	6.9	6.3	1	6.8	4.8	0.7	-0.1	1%
bl	3.1	2.5	1	3.0	2.1	0.9	0.5	0%
bm	0.0	0.0	0	0.0	0.0	0.0	0.0	91%
bn	0.0	0.0	0	0.0	0.0	0.0	0.0	0%
bo	193.6	181.8	1	191.1	118.7	69.8	45.4	0%
bp	0.1	0.1	1	0.1	0.1	0.0	0.0	0%
bq	5.2	4.9	1	5.1	3.3	1.1	-0.4	2%
br	0.2	0.2	0	0.2	0.2	0.2	0.2	0%
bs	0.5	0.5	0	0.5	0.4	0.3	0.1	0%
bt	1.0	1.0	0	1.0	0.9	0.9	0.9	0%
bu	0.0	0.0	0	0.0	0.0	0.0	0.0	34%
bv	5.3	5.1	1	5.3	5.0	3.3	1.8	1%
bw	0.0	0.0	0	0.0	0.0	0.0	0.0	0%
bx	0.8	0.8	0	0.8	0.8	0.6	0.5	0%
by	0.3	0.3	1	0.3	0.3	0.2	0.0	1%
bz	0.0	0.0	0	0.0	0.0	0.0	0.0	0%
ca	0.3	0.3	1	0.3	0.3	0.2	0.1	0%
cb	3.1	2.5	1	3.0	1.6	0.4	0.0	1%
cc	0.2	0.2	0	0.2	0.2	0.2	0.2	0%
cd	0.0	0.0	0	0.0	0.0	0.0	0.0	0%
aver.	14.8	12.8		14.4	8.9	4.7	2.5	2.5%
sum			33					33

Figure A.1 Bank size & 1st round impact

Impact (E_1 / B_0), share in total sectors' assets (x-axis)

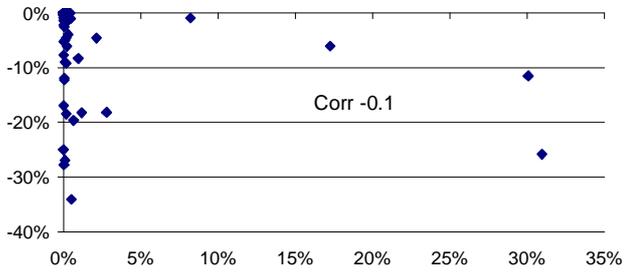
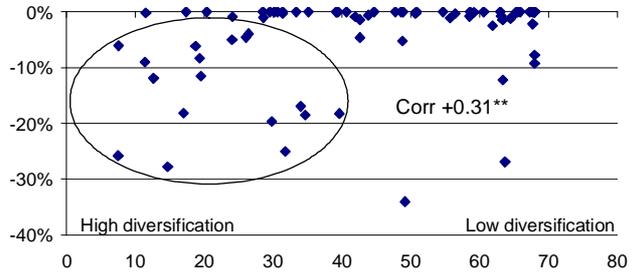


Figure A.2 Funding diversification & 1st round impact

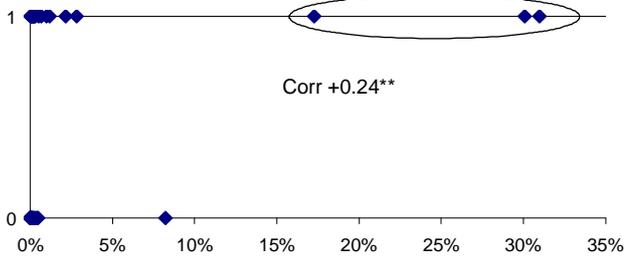
Impact (E_1 / B_0), kurtosis of funding structure (x-axis)



** significant at 5% confidence level

Figure A.3 Bank size & reaction

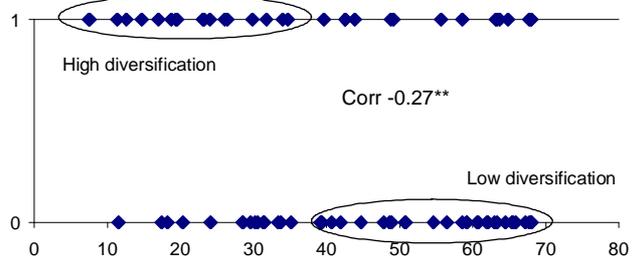
Trigger for reaction (0,1), share in total sectors' assets (x-axis)



** significant at 5% confidence level

Figure A.4 Funding diversification & reaction

Trigger for reaction (0,1), kurtosis of funding structure (x-axis)



** significant at 5% confidence level

Figure A.5 Bank size & shortfall probability

Probability $B_3 < 0$, share in total sectors' assets (x-axis)

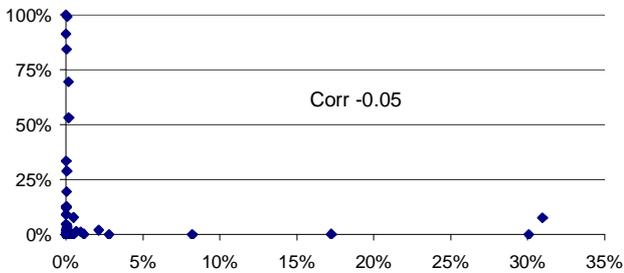
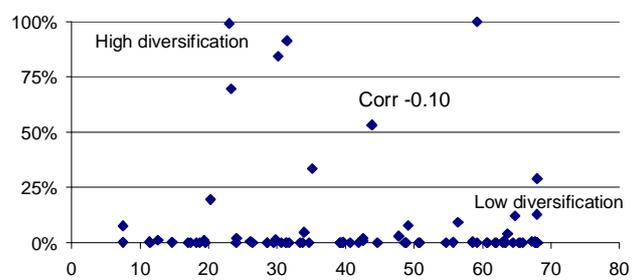


Figure A.6 Funding diversification & shortfall probability

Probability $B_3 < 0$, kurtosis of funding structure (x-axis)



Previous DNB Working Papers in 2008

- No. 163 **Carin van der Cruijssen and Sylvester Eijffinger**, Actual versus perceived transparency: the case of the European Central Bank
- No. 164 **Jacob Bikker and Janko Gorter**, Performance of the Dutch non-life insurance industry: competition, efficiency and focus
- No. 165 **Maarten van Rooij and Federica Teppa**, Choice or No Choice: What Explains the Attractiveness of Default Options?
- No. 166 **Peter Wierts**, How do Expenditure Rules affect Fiscal Behaviour?
- No. 167 **Jacob Bikker and Laura Spierdijk**, How Banking Competition Changed over Time
- No. 168 **Willem Heeringa**, Optimal life cycle investment with pay-as-you-go pension schemes: a portfolio approach
- No. 169 **Kerstin Bernoth, Andrew Hughes Hallett and John Lewis**, Did fiscal policy makers know what they were doing? Reassessing fiscal policy with real-time data
- No. 170 **Alan S. Blinder, Michael Ehrmann, Marcel Fratzscher, Jakob de Haan and David-Jan Jansen**, Central Bank Communication and Monetary Policy: A Survey of Theory and Evidence
- No. 171 **M. van Leuvensteijn, C. Kok Sørensen, J.A. Bikker and A.A.R.J.M. van Rixtel**, Impact of bank competition on the interest rate pass-through in the euro area
- No. 172 **Stijn Claessens and Neeltje van Horen**, Location Decisions of Foreign Banks and Institutional Competitive Advantage
- No. 173 **Peter Spreij, Enno Veerman and Peter Vlaar**, Multivariate Feller conditions in term structure models: Why do(n't) we care?
- No. 174 **Iman van Lelyveld and Klaas Knot**, Do financial conglomerates create or destroy value? Evidence for the EU

