When liquidity risk becomes a macro-prudential issue: Empirical evidence of bank behaviour
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Jan Willem van den End and Mostafa Tabbae *

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

This paper provides empirical evidence of behavioural responses by banks and their contribution to system-wide liquidity stress. Using firm-specific balance sheet data, we construct aggregate indicators of macro-prudential risk. Measures of size and herding show that balance sheet adjustments have been pro-cyclical in the crisis, while responses became increasingly dependent across banks and concentrated on certain market segments. Banks’ reactions were shaped by decreased risk tolerance and limited flexibility in risk management. Regression analysis confirms that their behaviour contributed to financial sector stress. The behavioural measures are useful tools for monetary and macro prudential analyses and can improve the micro foundations of financial stability models.

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

JEL Codes: C15, E44, G21, G32

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1. Introduction

The 2007-2009 crisis has shown that liquidity risk stemming from collective reactions by market participants can exacerbate financial instability. Liquidity hoarding by funding constrained banks added to the drying up of market liquidity. Through this channel liquidity risk led to solvency problems since banks had to write off illiquid assets. These developments have induced policymakers to focus on the interactions between funding and market liquidity risk and related systemic risk, as part of the macro-prudential approach (de Larosière, 2009). Getting a better grip on such dynamics requires an understanding of firms’ behaviour on a micro level in relation to macro-financial developments. In practice, liquidity risk is either analysed, managed and regulated from the perspective of banks’ funding positions (e.g. by supervisors) or on the level of the financial system as a whole (by central banks). However, recent events have underscored that systemic risk can originate at the nexus of funding and market liquidity, influenced by reactions of market participants.

This paper provides empirical evidence of behavioural responses by banks and their contribution to system-wide liquidity stress. The detrimental effects of liquidity risk are often driven by reactions of market participants to initial shocks. This is the endogenous cycle view of instability, where risk is endogenous with respect to collective behaviour of market participants. Their reactions can amplify shocks and generate instability. However, endogenous cycle models are still primitive, with very limited behavioural content (Borio and Drehmann, 2009). This also holds for macro stress-testing models that are used by central banks and supervisory authorities to simulate shocks to the system as a whole. Even in the most sophisticated stress-testing models, the behaviour of financial institutions is included by rules of thumb rather than through empirical estimations (e.g. Cifuentes, 2005; Aikman et al, 2009). An empirical foundation requires information on the effects of management actions on the stability of the financial system and the economy, based on both balance sheet data and market indicators in extreme situations. The recent crisis provides a rich set of such data, which helps to assess the assumptions in the literature on second round effects of banks’ management actions empirically.

To research the behaviour of banks, we construct aggregate measures with data of individual banks. This follows a macro-prudential approach. Herein, risks to the financial system as a whole can either be measured by aggregate balance sheet indicators (IMF, 2008), market prices or by composite indicators. All of these have their limitations in assessing common exposures and interactions (see Borio and Drehmann, 2009). We go a step further than traditional balance sheet indicators, by defining measures for behavioural reactions and testing them empirically. The main drivers of macro prudential risk are measured, i.e. the time dimension and the cross-sectional dimension. The time dimension is operationalised by indicators of size and direction of balance sheet adjustments as reflection of herding behaviour. The cross-sectional dimension is operationalised by indicators of the dependency of behaviour across banks and its concentration on market segments. Being based on common liquidity
exposures across institutions, the measures address a main shortcoming in analytical tools that focus on risks of cross-sectional exposures and pro-cyclicality (Borio, 2009). Applied to Dutch banks, the measures show that the size and number of responses (time dimension) and the dependency and concentration (cross-sectional dimension) substantially changed in the crisis. Regression analyses confirm that these behavioural dimensions reinforced the second round effects in the financial system.

The structure of the paper is as follows. Section 2 elaborates on the macro prudential approach and reviews related literature. Section 3 describes the data and developments of liquid assets and liabilities during the crisis. In section 4, measures of bank behaviour are constructed and empirical tests are performed. Section 5 presents outcomes of regression estimates on the systemic effects induced by banks’ behaviour. Section 6 concludes.

2. Literature

The relevance of behavioural reactions of market participants for financial stability is recognised in literature describing the macro-prudential approach. According to Borio (2006), this approach focuses on the financial system as a whole, including the underlying correlations. Dependencies relate to similar investments and risk management strategies of financial institutions that have common exposures. This cross-sectional dimension can be measured by the correlation between institutions’ balance sheets and by the marginal contribution of each institution to total systemic risk (Borio et al., 2009). Next to this cross-sectional dimension of aggregate risk, the macro-prudential approach distinguishes the time dimension. This concerns how risks evolve over time (which can be measured by macro economic variables like credit growth (BIS, 2009)) and whether pro-cyclicality plays a role. Pro-cyclicality can be caused by collective behaviour of financial institutions reinforcing interactions between the financial system and the real economy. In the literature these feedback mechanisms are attributed to rising risk tolerance, overextension of balance sheets and leverage during an expansion, which are reversed in a downturn. The increased ties between market and funding liquidity are another driving factor (e.g. through increased use of collateral in secured financing).

Adrian and Shin (2008) show that leverage is a driver for pro-cyclical management actions. A certain leverage target urges firms to expand their balance sheets when market prices go up and vice versa. Their paper identifies the growth of assets and repo positions as measures for aggregate liquidity. In this way, banks’ behaviour and market liquidity are linked. Adrian and Shin provide empirical evidence that this interplay elicits broader disturbing effects on financial markets. In Gromb and Vayanos (2008) the liquidity that arbitrageurs provide to the market depends on the level of their capital and leverage. Low returns on their investments makes leverage unsustainable and can lead to a drying up of market liquidity. Borio and Zhu (2008) attribute pro-cyclicality to the interconnectedness of liquidity and risk-taking. Changes in risk perceptions and risk tolerance influence external funding...
constraints. A loosening of liquidity conditions can induce firms to invest in high risk/return projects and vice versa. These cycles are reinforced by interactions between market and funding liquidity. Such dynamics are a central element in the work of Brunnermeier and Pedersen (2009) on margin constrained traders. They model ‘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.

Another strand of studies relates banks’ behaviour to central bank operations. The access to central bank liquidity has implications for banks’ behaviour and may introduce moral hazard. It can induce banks to hold lower levels of liquid assets and stimulate them to rely on other banks’ liquid assets (see Bhattacharya and Fulghieri, 1994, Repullo, 2005). Cao and Illing (2008) model the feedback from central bank liquidity provision to risk taking by financial intermediaries. The fall-back option of central bank liquidity gives banks an incentive to free ride and invest in illiquid projects. In this model liquidity shocks are endogenous. Drehman and Nikolaou (2009) take banks’ bidding on central bank money as a measure for funding liquidity. This is used as a proxy to empirically investigate the link between funding and market liquidity that is driven by balance sheet adjustments of banks.

In macro stress-testing models, behavioural reactions of financial institutions are mostly based on calibrations and rules of thumb. Responses are usually triggered by shocks that lead to a declining solvency ratio of banks below a certain threshold level. This default risk can be caused by a drying up of market liquidity which depresses the value of banks’ assets, as in Cifuentes et al (2005). This triggers fire sales of assets, depressing market prices and inducing further sales. Default risk is also a trigger for portfolio adjustments by banks in the stress-testing framework of the Oesterreichische Nationalbank (Boss et al, 2006). In a recent version of the macro stress-testing model of the Bank of England, behavioural responses are related to funding liquidity risks of banks (Aikman et al, 2009). In this model, funding strains increase the default risk of banks, which may at a certain stress level resort to fire sales of assets. This leads to liquidity feedbacks through depressed market prices of assets. In the Liquidity Stress-Tester model of Van den End (2008), feedbacks between market and funding liquidity risk are driving the second round effects of market disturbances on banks. Banks’ responses are assumed to be triggered by a certain decline of the liquidity buffer. In this model, the second round effects are mechanically determined by the number and size of reacting banks and the similarity of reactions.
3. Data and trends

3.1 Data
In the rest of this paper, several of the assumptions of bank behaviour as applied in the literature are empirically tested with data of liquid assets and liabilities of banks. Our sample consists of Dutch banks, of which DNB’s supervisory liquidity report provide a detailed break-down of liquid assets and liabilities and cash in and outflows. The report includes on and off-balance sheet items for all Dutch banks (85 on average, including subsidiaries of foreign banks) with a rather detailed break-down per item (average granularity of around 7 items per bank). The monthly data cover the 2003m10 - 2009m3 period. The various balance sheet and cash flow items in the prudential report are assumed to reflect the instruments (i) which banks (b) use in the liquidity risk management in response to shocks. The instruments are expressed in gross amounts ($I_b^i$). Shocks can affect the banks through declining liquidity values of liquid assets and reduced cash inflows in stressed market conditions. Liabilities can be affected in a stress scenario through calls on contingent liquidity lines, withdrawals of deposits, drying up of wholesale funding and changes of liabilities due to derivatives. The net position in liquid assets and liabilities shows up in the liquidity buffer ($B_b^d$) of a bank. According to DNB’s prudential liquidity requirement, banks should have a liquidity surplus at both a one week and a one month horizon.

3.2 Trends
The data provide a rich source of information on the liquidity management of banks. Management actions have been influenced by market developments, but have also - endogenously - contributed to it. Two main trends in the behaviour of banks in the crisis appear from the data:

i) contraction of balance sheets through reduced repo positions and sales of tradable securities;

ii) increased liquidity assurance through changed funding structures and reliance on central bank facilities.

These trends have been influenced by the different stages of the crisis. In each phase, the nature of liquidity risk changed, to which the banks anticipated in their management actions. In the first stage (August 2007 until the demise of Bear Stearns in March 2008) market liquidity dried up, which interacted with the funding liquidity of banks. The second stage (between March 2008 and failure of Lehman in September 2008) was characterised by increased counterparty risks due to concerns about bank failures, while in the third phase (October 2008 until March 2009) liquidity stress spilled over into solvency problems of banks on the back of a rapid economic slow-down. Since March 2009, financial markets have shown a recovery.
3.3 Balance sheet contraction

The most obvious response of the banks to the crisis was a marked reduction of secured lending and borrowing (repo, reverse repo and securities lending transactions, see Figure 1). These transactions grew rapidly before the crisis, when booming asset prices stirred up credit supply collateralised by tradable securities. Hence, our data confirm the conclusion of Adrian and Shin (2007), that buoyant repo transactions increased the liquidity in the financial system. The strong reduction of secured lending and borrowing since the crisis reflects the acute stress on markets, in particular the drying up of the interbank market, which urged banks to shrink their balance sheets and to deleverage. Secured positions were reduced in particular in the second stage of the crisis, when counterparty risks mounted and only of the highest collateral quality was accepted in repo transactions.

The strong decline of secured borrowing and lending contrasts to the development of unsecured positions, which still grew until Autumn 2008 and only modestly declined in the third stage of the crisis. One would expect that unsecured positions are sensitive to market turbulence and risk aversion. However, the data show that secured financing is more pro-cyclical instead, due to its dependence on market values of collateral. Unsecured wholesale lending to non-banks even expanded, since these clients drew on their credit lines more actively (such as strained investors that had to meet margin requirements). Retail credit supply also held up relatively well; annual growth has remained positive in each stage of the crisis, even excluding loans that could not be securitised anymore. This confirms a pecking order in banks’ balance sheet management, which says that retail credits are only curtailed if there are no other options left.

Balance sheets also shrunk because trading portfolios were scaled back. Figure 2 shows that the decline of portfolio values outpaced the fall of the market prices, indicating that banks actively sold their trading portfolios, which exerted a pro-cyclical influence on markets. In each stage of the crisis these exposures declined; fixed income investment in particular in the first phase and equity holdings...
primarily since Lehmann. In the third crisis stage derivative positions were also reduced significantly, partly due to tear-ups (cancellations of contracts outstanding between dealers) in reaction on the demise of Lehmann, which was a main dealer bank in the derivative market. Investment portfolios were reduced to de-risk balance sheets, reduce counterparty exposures and to free up liquidity by selling assets and lowering trading limits (reclassification of exposures from trading to banking books was not substantial in the case of Dutch banks). This outpaced the increase of bond portfolios due to internal securitisation by banks to create securities eligible for pledging at the central bank. This activity did enhance the underlying credit quality of the portfolios (the share of Tier 1 securities in the aggregate bond portfolio doubled to nearly 60% during the crisis).

3.4 Assurance of funding liquidity

A second trend in the crisis was that banks changed their funding structure to secure the availability of liquidity. Wholesale funding fell back in each stage of the crisis (Figure 1). This was partly compensated by an increase of retail savings. Until October 2008 demand deposits were primarily substituted by fixed term deposits, but in the third stage of the crisis banks were also able to attract a higher level of retail savings in total, which provided a more stable source of liquidity.

Liquidity was also safeguarded by an increased reliance on central bank facilities. In the beginning of the crisis, banks had to take back highly rated assets from off-balance sheet vehicles, for which market liquidity had dried up. Banks acted as shock absorbers by providing a substitute to market liquidity. However, this caused market illiquidity to spill over into funding liquidity, since the returning assets had to be funded by the banks. In response, they increasingly created ECB eligible securities by internal securitisation of corporate loans and mortgages, to enhance the tradability of these assets. Besides, banks stepped up the use of their ECB deposit facility, in particular in the first stage of the crisis, when the interbank market dried up and ECB increased its intermediary function.
4. Empirical measures

In this section, the trends in the behaviour of banks are described by empirical measures, based on firm-specific balance sheet data. First, we define and test the trigger for management actions and the type of instruments used to respond. Second, empirical metrics are constructed to describe the macro prudential dimensions of behaviour. Measures of the size and number (i.e. herding) of reactions are defined to reflect the time dimension. Measures of the dependency of banks’ responses and their concentration on market segments reflect the cross-sectional dimension. The measures are applied to different market segments to explain the behaviour of banks in more detail.

4.1 Threshold of risk tolerance

As a trigger for reaction, we define the decline of the liquidity buffer \((B)\) that exceeds a certain threshold (following mechanical response rules as in Aikman et al, 2009 and Van den End, 2008). The threshold level is operationalised by the correlation between relative changes in balance sheet items 
\[
\left( \frac{b_{1,t} - b_{1,t-1}}{I_{i,t-1}}, \text{ reflecting bank's intentional responses} \right)
\]
and declines in liquidity buffers 
\[
\left( \frac{b_{2,t} - b_{1,t-2}}{B_{1,t-2}} \right), \text{ one month lagged (the lag controls for the influence of possible endogeneity in the relationship between the buffers and the change of balance sheet items; endogeneity is further tested in section 5.1).}
\]
This assumes that banks who are affected by a certain decline of their liquidity buffer, respond to a stress scenario by adjusting their balance sheet to restore their liquidity position. The liquidity buffer is a likely trigger for this, as it functions as a liquidity risk standard for banks, supervisors and rating agencies. We test whether the correlation was influenced by the crisis. We use the non-parametric Spearman correlation, since this statistic does not require assumptions about the distribution of the data and is less sensitive to outliers. This is relevant with regard to our dataset, since both the item and the buffer changes are not normally distributed (see Figures 3a and 3b, of which the right tail is caused by small banks with outliers of relative changes due to denominator effects). Since the correlation is based on monthly changes of balance sheet items and buffers, it is not influenced by structural changes of the composition of balance sheets.

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1 The classification of items follows the broad definitions in Figure 1. In the empirical analyses in this section a more detailed break-down of items is used, according to the number of entries in the liquidity report, which distinguishes 81 different balance sheet items per bank. Since most banks do not report all items, the average number of reported items is seven.

2 The Cramer-von Mises (MvS) and Anderson-Darlin (AD) normality tests are used. ***, **, * denotes rejection of normality at 1%, 5%, 10% confidence level.
Over the whole sample period it appears that only substantial declines of the liquidity buffer (60 to 70%) were significantly correlated with balance sheet adjustments (Table 1). In 2007m7 – 2009m3 this correlation coefficient increased and the sign reversed, the latter indicating that the nature of banks’ reactions changed due to actions to safeguard liquidity and deleverage balance sheets. The increased correlation coefficient in the crisis suggests a strengthened link between banks’ reactions and market volatility and thereby an increased likelihood of pro-cyclical management actions. Figure 4 confirms that during the most stressful episodes of the crisis the number of banks with substantial declines of liquidity buffers increased and thereby their need for contingency actions.

Table 1
Correlation between balance sheet items (I) and lagged relative change of buffer (B)

<table>
<thead>
<tr>
<th>Buffer change (%)</th>
<th>2003-10 .. 2009-3</th>
<th>2007-7 .. 2009-3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs</td>
<td>Correl coef</td>
</tr>
<tr>
<td>0 - 10</td>
<td>28349</td>
<td>0.00</td>
</tr>
<tr>
<td>10 - 20</td>
<td>8628</td>
<td>0.01</td>
</tr>
<tr>
<td>20 - 30</td>
<td>3560</td>
<td>0.01</td>
</tr>
<tr>
<td>30 - 40</td>
<td>2240</td>
<td>-0.01</td>
</tr>
<tr>
<td>40 - 50</td>
<td>1166</td>
<td>-0.01</td>
</tr>
<tr>
<td>50 - 60</td>
<td>763</td>
<td>-0.02</td>
</tr>
<tr>
<td>60 - 70</td>
<td>646</td>
<td>0.08**</td>
</tr>
<tr>
<td>≥ 70</td>
<td>637</td>
<td>0.05</td>
</tr>
</tbody>
</table>

***, **, * significant at 1%, 5%, 10% confidence level
Based on all Dutch banks, monthly periods

It is remarkable that in the crisis, banks also tended to react to small changes of liquidity buffers (10 to 20%), as indicated by the significant correlation coefficient in the 2007m7-2009m3 period (Table 1). The correlation was not significant in the period before, as in normal market circumstances small
shocks are (passively) absorbed by the available liquidity buffers, while in stressful markets banks are inclined to react to small movements in their liquidity position to limit their vulnerability to market shocks. This is concomitant to the liquidity hoarding by banks during the crisis and indicates that stressed market conditions raise banks’ nervousness about their liquidity buffers. Or stated otherwise, a decreasing risk tolerance in stressed markets contributes to pro-cyclical management actions.

4.2 Instruments used to react

The influence of behaviour on markets also depends on banks’ risk management strategies. To assess how these changed in the crisis, we test the hypothesis that banks react with instruments proportional to the composition of their balance sheet \( \frac{I_i}{\sum_i I_i} \), as in van den End (2008). This assumes that the balance sheet composition determines the availability of liquidity instruments, as a reflection of banks’ specialisation and presence in certain market segments. This rather mechanical assumption does not take into account the different accessibility of market in a crisis. However, in stress situations banks have few opportunities to adapt their strategy in the short run (e.g. by diversifying funding and entering new markets) and therefore will resort to instruments readily at their disposal. The ‘mechanical reaction hypothesis’ can be formulated as,

\[
\Delta I_i, \Delta \sum_i I_i = \frac{I_i}{\sum_i I_i}
\]

which says that banks react by an instrument (reflected in the relative change of the value \( I \) of that balance sheet item \( i \)) in absolute terms, i.e. the term on the left hand side) according to the composition of their balance sheet (i.e. the right hand side of the equivalence). A sign test is performed to see whether the ratio on the left hand side of equation 5 is equal to the ratio on the right hand side. The test is performed at the level of each item \( i \), by testing the null hypothesis that the median of \( x(i)^1, x(i)^2, ..., x(i)^n \) is equal to 0 (with \( x(i) \) being the difference between the left hand side and right hand side of equation 5), for bank \( 1..n \), based on monthly data, or,

\[
H_0: \left| \frac{\Delta I_i, \Delta \sum_i I_i}{\sum_i I_i} \right| - \frac{I_i}{\sum_i I_i} = 0
\]

Under the null hypothesis we would expect half of the \( x \)'s to be above the median and half below. Again we use a non-parametric test to take into account the fact that the sample of \( x(i)^1, x(i)^2, ..., x(i)^n \) is not normally distributed.  

\[3\] Normality is rejected by the Cramer-von Mises (MvS) and Anderson-Darlin (AD) tests at a 1% confidence level.
Table 2 summarises the test outcomes by providing the number of cases (i.e. items) in which the hypothesis is rejected relative to the number of cases in which it is accepted. The Table shows that the equivalence is rejected in most cases in the sample period, although the break-down by bank size shows that it holds in nearly 50% of the cases for small banks. This suggests that they have limited flexibility in their liquidity risk management and resort to instruments according to the composition of their balance sheet. It is striking that in the crisis, the null hypothesis is accepted in the majority of cases for the whole population of banks. This is most dominant for small banks, but the equivalence is accepted by an increased number of medium sized and large banks as well (Table 2). It indicates that in turbulent market conditions banks in general have less flexibility to change tack and therefore resort to readily available sources of liquidity. This finding underscores that such a mechanical rule in stress-testing models are particularly suited for stress situations.

<table>
<thead>
<tr>
<th>Table 2, Test of equivalence of banks’ reaction function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sign test of $\left(\frac{\Delta I_i}{\sum \Delta I_i} \right) = \left(\frac{I_i}{\sum I_i}\right)$</td>
</tr>
<tr>
<td>Percentage of banks were equivalence holds, according to sign test, 5% confidence interval</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>2003m10-2009m3</th>
<th>2007m7-2009m3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All banks</td>
<td>Small</td>
</tr>
<tr>
<td>Equivalent</td>
<td>30%</td>
<td>48%</td>
</tr>
<tr>
<td>Not Equivalent</td>
<td>70%</td>
<td>52%</td>
</tr>
<tr>
<td>Observations</td>
<td>96829</td>
<td>7129</td>
</tr>
</tbody>
</table>

Note: the break-down between small, medium sized and large banks is based on the sum of balance sheet items per bank, small banks have less observations than larger banks because small banks usually report less items in the supervisory report.

4.3 Size of reactions

Besides the type of instruments which banks use to react, market stability can also be influenced by the size of their transactions. This could indicate the build up (or unwinding) of imbalanced exposures and leverage, both being potential drivers of pro-cyclicality. Thereby the size of the balance sheet adjustments represents the time dimension of macro prudential risk. Size is approximated by $S_{r,t}$ (weighted average relative monthly change of balance sheet items, averaged across items and banks) and by $S_{m,t}$ (median of relative monthly item changes, per bank, per item),

$$S_{r,t} = \frac{\sum \sum \Delta I^{b}_{i,t}}{n+x} / \frac{\sum \sum I^{b}_{i,t}}{n+x} \quad (7)$$

$$S_{m,t} = \text{median} \left( \Delta I^{b(1)}_{i(1),t} / I^{b(1)}_{i(1),t} \ldots \Delta I^{b(n)}_{i(n),t} / I^{b(n)}_{i(n),t} \right) \quad (8)$$
with \( x \) being the total number of balance sheet items \((i)\) and \( n \) the total number of banks \((b)\). Figures 5 and 6 show that in the years before the crisis, Dutch banks expanded their balance sheets, with \( S_{r,t} \) being positive until the start of the crisis and \( S_{m,t} \) until the end of the second crisis stage. The difference between \( S_{r,t} \) and \( S_{m,t} \) indicate that large banks (which dominate \( S_{r,t} \) since this is a weighted measure) had expanded their balance sheets more vigorously before the crisis than smaller banks and started to unwind their exposures at an earlier stage in the crisis. The downward trend indicates the substantial balance sheet adjustments conducted by the banks. Both measures fell rapidly, even exceeding two standard deviations in the third stage of the crisis. This indicates the asymmetric nature of banks’ behaviour: being more intense in busts than in booms. This deleveraging process seems to have run its course since March 2009, the end of the third crisis stage. Large banks seemed to be most advanced in deleveraging their balance sheets, as indicated by the upturn of \( S_{r,t} \) in Figure 5.

4.4 Herding: number of reactions

The number of reacting banks is a driver for systemic risk, as it reflects the collectively of banks’ responses to liquidity stress. If such herding behaviour goes in one direction, it can cause procyclicality in financial markets. Thereby it is another indication of the time-dimension of macro prudential risk. Measures of herding in the literature usually apply to financial market trades and not to behaviour of banks (applied to banks, herding is usually associated to bank runs by depositors, like in Allen and Gale, 1998). Based on market indicators of herding, we reconstruct a metric to assess whether there has been herding by our sample of banks. This statistical indicator resembles the herding measure of Lakonishok, Shleifer and Vishney (LSV, 1992), as applied by Bikhchandani and Sharma (2001) amongst others. The LSV measure is defined as the number of investors who buy or sell a

\[ \text{Herding: number of reactions} \]

\[
\text{The value change of a balance sheets item is corrected for changes of related market prices, to reflect volume changes and to get a better indication of deliberate portfolio adjustments. This is only done for exposures held for trading and available for sales, since other exposures are not classified as mark-to market.} \]

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stock relative to the average number of investors trading in the stock market. Compared to stock market trades, a distinction between positive and negative adjustments in the balance sheets of banks is not obvious, since the direction of a management action will be determined by the nature of balance sheet item (for instance it can be expected that a balance sheet item $j$ will be reduced in a crisis, while another balance sheet item $k$ will be expanded, depending on whether an item is an asset or liability, a stable or unstable source of liquidity etc.). The different nature of balance sheet items is taking into account in the analysis by market segment in section 4.6. For the purpose of an aggregate herding measure, we define $H_{b,t}$ as the total number of banks that make one or more extreme positive and negative changes to their balance sheet items, measured by value changes of items that exceed a threshold $z$,

$$H_{b,t} = \sum_{y_i > z} f(y_i)$$  \hfill (9)

with $y_i$ for each balance sheet item being the ratio $\frac{\Delta I_{i,t}^b}{\sum b \Delta I_{i,t}^b / n}$, and $z$ being the cut-off point at the 5% tail of the distribution of this ratio. Figure 7 indicates that in the crisis the number of banks with an extreme response ($H_{b,c}$) was much higher than in the years before, pointing at increased herding. The break-down of $H_{b,t}$ in Figure 8 shows that this was driven by increased downward adjustments of balance sheet items, while before the crisis the number of banks with extreme upward adjustments was substantially higher. It indicates that the directional change of herding shifted from extension to contraction of balance sheets.

In Figures 7-10 $H_{t}$ and $H_{i}$ are based on the 10% largest items in terms of value, to filter for large relative changes that are related to a small denominator value of the ratio.
By also including in $H$ the multiple swings of balance sheet items on account of one bank, we construct $H_{i,t}$ (Figure 9). Both $H_{b,t}$ and $H_{i,t}$ peaked in the crisis, while the break-down of $H_{i,t}$ in Figure 10 confirms that the direction of herding changed from positive to negative in the crisis. This reflects that in the 2005-2007 period, there was an increased number of extreme actions to extend balance sheets (for instance to high yielding exposures), followed by an intense unwinding in the crisis.

4.5 Dependency of reactions

The cross-sectional dimension of macro prudential risk is measured by the dependency of bank’ behaviour. First, a dependency measure ($D_{c,t}$) is determined by the correlations between balance sheet item changes of all banks. It follows the few studies in which causalities between loan portfolios of banks are analysed (like in Nakagawa and Uchida (2007) for Japanese banks and Jain and Gupta (1987) for US banks). $D_{c,t}$ is based on the relative changes ($S_{r,i}$) of each balance sheet item $i$, $j$...$x$, per bank. Bilateral correlations between changes of balance sheet item ($i$) with changes of other items ($j..x$) are calculated across banks $1..n$, per month. $D_{c,t}$ is then constructed by averaging the bilateral correlations in the matrix below, for each month,

$$
\begin{align*}
\text{Item } i & \quad \text{Item } j & \quad \text{Item } k & \quad \ldots & \quad \text{Item } x \\
\text{Item } i & \quad \text{Cor} (S_{r,i}, S_{r,j}) & \quad \text{Cor} (S_{r,i}, S_{r,k}) & \quad \ldots & \quad \text{Cor} (S_{r,i}, S_{r,x}) \\
\text{Item } j & \quad \text{Cor} (S_{r,j}, S_{r,i}) & \quad \text{Cor} (S_{r,j}, S_{r,k}) & \quad \ldots & \quad \text{Cor} (S_{r,j}, S_{r,x}) \\
\text{Item } k & \quad \text{Cor} (S_{r,k}, S_{r,i}) & \quad \text{Cor} (S_{r,k}, S_{r,j}) & \quad \ldots & \quad \text{Cor} (S_{r,k}, S_{r,x}) \\
\ldots & \quad \ldots & \quad \ldots & \quad \ldots & \quad \ldots \\
\text{Item } x & \quad \text{Cor} (S_{r,x}, S_{r,i}) & \quad \text{Cor} (S_{r,x}, S_{r,j}) & \quad \text{Cor} (S_{r,x}, S_{r,k}) & \quad \ldots
\end{align*}
$$

$^6$ To get the relative change of each balance sheet item separately, the summation sign $\sum_{i}$ is dropped from the numerator and $i$ is dropped from the denominator in equation 7.
Second, the correlation structure between balance sheet item changes is extracted by factor analysis. We define $D_{f,t}$ as the common driver of the relative changes $S_{r,t}(i)$, of balance sheet items $i, j...x$, across bank. $D_{f,t}$ is determined by the eigenvalue of the first factor of the factor analysis, indicating the variance that is explained by this factor.

Like the herding measures described in the previous section, $D_{c,t}$ and $D_{f,t}$ peaked in the crisis (Figures 11 and 12). Nonetheless, the dependency measures lagged behind the herding measures, as $H_{b,t}$ and $H_{i,t}$ were close to their peaks already in the first stage of the crisis. $D_{c,t}$ and $D_{f,t}$ accelerated in the second stage, when counterparty risks increased and banks hoarded liquidity, confirming an increased correlation between bank’s behavioural reactions in that period.

4.6 Behaviour on market segments

The cross-sectional dimension of banks’ behaviour can further be explored by relating the size of transactions conducted by a particular balance sheet item to the overall balance sheet adjustments. This gives an impression of the similarity of reactions and the concentration of trades in particular market segments. This could indicate the build up of common exposures by banks (or vice versa concerted withdrawals from markets). Empirically this variable is approximated by the concentration measure $C_t(i)$:

$$C_t(i) = \frac{\sum_b |\Delta I^b_I|}{n} / \frac{\sum_i \sum_b |\Delta I^b_{i,t}|}{n + x}$$

With $C_t(i)$ being the proportion of balance sheet adjustments that is concentrated on a market segment $i$. The adjustment can be downward or upward, depending on the nature of the balance sheet item. By
using absolute values we control for the sign of the adjustment, because $C(i)$ intends to measure transactions volumes, irrespective of their direction.

To assess potential distortions due to behavioural actions in more detail, the measures for size ($S_{r,t}(i)$), herding ($H_{b,t}(i)$) and concentration ($C_t(i)$) are applied to different market segments. The Figures in Annex 1-3 show that in the crisis, typical balance sheet adjustments took place in the various market segments. The first trend is an increased reliance on the central bank, both for bank’s deposits and funding. This was reflected in an increased concentration of transactions with the central bank ($C_t(i)$ in Figure 13), owing to an increased number of banks ($H_t(i)$ in Figure 14). The oscillating pattern of the size measure $S_{r,t}(i)$ in Figures 15 and 16 relates to the money market policy of the ECB. The central bank created excess liquidity at the start of a maintenance period and gradually scaled it back during that period. The creation of excess liquidity is reflected in the upward spikes in Figures 15 and 16 and vice versa for the scaling back of market liquidity. Over the maintenance period, banks parked the excess reserves partly at the ECB deposit facility, which shows in up in a negative relationship between the size measure for claims and the one for borrowing from the central bank.

---

7 This is done by constructing $S_{r,t}(i)$ and $H_b(i)$ for each balance sheet item ($i$) separately, by dropping the summation sign $\sum$ from the numerators and $x$ from the denominators of the ratios in equations 7 and 9 (the concentration measure $C_t$ is originally constructed on the level of market segments in equation 10).
The measures also show the multiple dimensions of the second trend of bank’s behaviour in the crisis, i.e. the deleveraging of balance sheets. The size of equity holdings ($S_{r,t}(i)$ in Figure 17) and bond portfolios (Annex 1) was reduced. This was not due to increased herding; the number of banks making extreme adjustment to their equity holdings remained low ($H_{b}(i)$ in Figure 18). This indicates that the reduction of equity holdings was concentrated at a limited number of banks. In the course of 2008, the overall reactions of banks became less concentrated in the stock and bond markets (see $C_{t}(i)$ in Annex 2). Probably, fire sales were prevented thanks to the extended ECB collateral criteria. These enhanced the liquidity value of a wider range of tradable assets for repos with the ECB.

![Figure 17 Relative size: equity holdings in trading books](image17.png)
**Size measure (Sr), 6 mth mov. aver.**

![Figure 18 Number of banks reacting: equity holdings](image18.png)
**Herding indicator Hb (6 mth mov. av.)**

The main factor behind deleveraging in terms of size was secured lending and borrowing, with $S_{r,t}(i)$ in Figure 19 even surpassing three standard deviations at the peak of the crisis in Autumn 2008. In that period, repos represented around ¼ of the overall change in balance sheets ($C_{t}(i)$ in Figure 20). Herding was less evident. The number of banks that made extreme adjustments to their repo positions did not increase markedly ($H_{b}(i)$ in Annex 3). This underlines that while leverage based on repo transactions was concentrated at a limited group of large banks operating in wholesale markets (amongst other market participants), so was the unwinding of the positions.

![Figure 19 Relative size: secured wholesale lending](image19.png)
**Size measure (Sr), 6 mth mov. aver.**

![Figure 20 Crowded trades: secured wholesale lending](image20.png)
**$C(i)$ indicator, 6 mth mov. av.**
With regard to the third trend - changed funding structures -, the herding measures in Figures 21 and 22 show that an increasing number of banks experienced substantial changes in their deposit funding base, due to volatile in and outflows. This reflects the increased mobility of deposits and the scramble for this funding source by a growing herd of banks that was looking for alternative funding sources. The aggressive bidding on (foremost fixed term) deposits stirred up retail deposit rates and caused turbulence in the Dutch retail savings market in the second half of 2008.

Figure 21 Number of banks reacting: wholesale demand deposits. Herding indicator Hb (6 mth mov. av.)

![Figure 21](image1)

Figure 22 Number of banks reacting: retail demand deposits. Herding indicator Hb (6 mth mov. av.)

![Figure 22](image2)

5. Estimation results

5.1 Endogeneity

A conceptual challenge concerning the behavioural measures is endogeneity, as changes in balance sheets could either be the resultant of market events, or market stress can be influenced by banks’ responses. It is hard to disentangle the effects of market developments and behavioural reactions of institutions, since these mutually interact.\(^8\) Endogeneity implies that behavioural reactions could either be lagging or leading to market stress. In the latter case they could reinforce market turbulence.

To get an impression of the sequencing of market stress and bank behaviour, Table 3 shows the leads and lags of peak correlations between both kinds of variables. Indicators for market-wide developments \((Mar)\) are the implied stock price volatility (VIX index) and corporate bond spreads \((Baa)\). As financial sector measures \((Fin)\) we use an index of credit default swap spreads \((CDS)\) and

\(^8\) In the construction of the empirical measures, endogeneity is circumvented to some extent, since the value changes of balance sheet items are corrected for market price developments to ensure that they measure volume changes (see footnote 4). Secondly, we focus on the extreme intervals of the measures, which better reflect intended balance sheet adjustments and hence active behaviour. And thirdly, by working with aggregate measures (based on micro data) the influence of idiosyncratic bank runs (which would falsely show up as a behavioural reaction in the measures) is reduced, since the liquidity run-off at one bank would possibly flow to other banks.
interbank Euribor spreads. It appears that the behavioural measures are significantly correlated with the market variables (Table 3, C_t is not included since it measures behaviour on the level of market segments). The herding measures $H_b,t$ and $H_i,t$ and the dependency measure $D_{f,t}$ are most closely correlated to the market variables and leading in most cases, while the size measures $S_{m,t}$ and $S_{r,t}$ are mostly lagging. The alternation of the leads and lags of the peak correlations suggests that there is endogeneity between banks’ behaviour and market developments. To formally detect endogeneity, a Hausman test is performed. First, the behavioural measures and $S_t, H_t$ and $D_t$ are regressed on their lagged values which are used as instrumental variables, as in equation 11.\(^9\)

$$S_t = \alpha + \beta_1 S_{t-1} + \ldots + \beta_m S_{t-m} + e_t$$ \hspace{1cm} (11)

The number of lags in the equation is chosen by a general-to-specific method. In first instance, 12 monthly lags are included. The significant lags between the first lag and the last significant lag were maintained. The residuals $e$ are then included in regression equations that explain the market-wide ($Mar_t$) and financial sector variables ($Fin_t$), both in terms of logs, out of the behaviour measures $S_t, H_t$ and $D_t$, as in equation 12.\(^10\)

$$Mar_t = \alpha + \beta S_t + \gamma e_t + \mu_t$$ \hspace{1cm} (12)

According to the Hausman test, endogeneity is rejected if the coefficients of $e$ are not significant. Table 3 shows that this is true for the size measures and the dependency measure based on factor analysis ($D_{f,t}$). However, endogeneity is accepted with regards to the herding measures ($H_b,t$ and $H_i,t$) and the dependency measure based on correlations ($D_{c,t}$), of which the coefficients $\gamma$ are highly significant. This result confirms endogeneity between the market-wide and financial sector variables on the one hand and behavioural measures (i.e. herding and dependency) on the other hand. Both sides of this mutual dependency are further explored in the next sections.

---

\(^9\) The VIX index is the CBOE Volatility Index, which is a key measure of market expectations of near-term volatility conveyed by S&P 500 stock index option prices. Corporate bond spreads are based on the Moody’s Baa industrial bond rates of US corporations. The CDS spread index is composed by the five years (most liquid segment) spreads of a group of large international financial institutions. Euribor spread refers to the three month spread between the Euribor rate and the Eonia swap spread. Source of both series is Bloomberg. Euribor spreads of Dutch banks are also available; this series has a correlation of nearly 1 with the market-wide Euribor spread. We have also constructed a CDS spread of Dutch banks, weighted by balance sheet total. This index is also closely correlated with the CDS index of international banks (indices in log terms have a correlation of 0.97, period 2004m1-2009m3).

\(^10\) Lags can be used as instrumental variables based on the a priori assumption that they are not correlated with the current residuals, because these were realised after the time periods when the lagged observations had materialised.

\(^11\) The log levels of the variables $Mar_t$ and $Fin_t$ are in most cases cointegrated with variables $S_t, H_t$, and $D_t$ according to the Johansen cointegration test.
Table 3, Statistics of behavioural measures
Based on 2003m10-2009m3 period

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Size</th>
<th>Herding</th>
<th>Dependency</th>
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<tbody>
<tr>
<td></td>
<td>$S_{it}$</td>
<td>$S_{mt}$</td>
<td>$H_{bt}$</td>
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<tr>
<td>Obs</td>
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<td>66</td>
<td>66</td>
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<tr>
<td>Mean</td>
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<td>0.001</td>
<td>39.0</td>
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<tr>
<td>Median</td>
<td>0.005</td>
<td>0.001</td>
<td>38.0</td>
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<tr>
<td>St dev.</td>
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<td>0.006</td>
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<table>
<thead>
<tr>
<th>Correlations</th>
<th>VIX</th>
<th>Credit spread</th>
<th>CDS spread</th>
<th>Euribor spread</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.42*** (+1)</td>
<td>-0.13* (-1)</td>
<td>-0.42*** (0)</td>
<td>-0.47*** (+1)</td>
<td></td>
</tr>
<tr>
<td>-0.36** (+1)</td>
<td>-0.24* (+2)</td>
<td>-0.35** (+3)</td>
<td>-0.31** (+2)</td>
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</tr>
<tr>
<td>0.60*** (-1)</td>
<td>-0.22* (+4)</td>
<td>0.83*** (-3)</td>
<td>0.68*** (-4)</td>
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</tr>
<tr>
<td>0.56*** (-3)</td>
<td>0.46*** (+4)</td>
<td>0.50*** (-2)</td>
<td>0.67*** (+2)</td>
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</tr>
<tr>
<td>0.31** (-4)</td>
<td>0.19* (-3)</td>
<td>0.32** (-2)</td>
<td>0.36** (-3)</td>
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</tr>
<tr>
<td>0.70*** (-4)</td>
<td>0.39*** (-3)</td>
<td>0.64*** (-2)</td>
<td>0.65*** (-4)</td>
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<table>
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<th>CDS spread</th>
<th>Euribor spread</th>
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<td>0.83</td>
<td>0.67</td>
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<td>0.00***</td>
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</tr>
<tr>
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<td>0.02**</td>
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<table>
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<th>Trend ($\beta$)</th>
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<td>0.00***</td>
<td></td>
</tr>
<tr>
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<td>0.00***</td>
<td></td>
</tr>
<tr>
<td>0.06*</td>
<td>0.12</td>
<td></td>
</tr>
<tr>
<td>0.00***</td>
<td>0.00***</td>
<td></td>
</tr>
<tr>
<td>0.00***</td>
<td>0.00***</td>
<td></td>
</tr>
<tr>
<td>0.02**</td>
<td>0.51</td>
<td></td>
</tr>
<tr>
<td>0.03**</td>
<td>0.03**</td>
<td></td>
</tr>
</tbody>
</table>

1 Correl.coef (peak corre; lead (-1) or lag (+1) of behaviour in months between brackets)
2 P-values of residual coefficient ($\gamma$) of equation 12 (endogeneity rejected if not significant)
3 P-values of regression coefficients of equation 13, size, herding and dependency measures as 3 mnt moving averages

***, **, * significant at 1%, 5%, 10% confidence level

5.2 Structural breaks

To test one side of the endogeneity - the influence of the crisis on balance sheets and hence on the behavioural measures - we follow a simple approach to estimate whether a break in the level or the trend of $S_t$, $H_t$ and $D_t$ can be identified. This is performed by estimating the equation (following Cecchetti et al, 2009),

$$S_t = \alpha + \alpha d_t + \beta t + \beta d_t t + \varepsilon_t$$  \hspace{1cm} (13)$$

with $d_t$ a dummy variable that is 1 in 2007m7 - 2009m3 and 0 before, and $t$ being the deterministic trend. Table 3 shows the results of the estimates $\alpha$ and $\beta$ (the estimated breaks in the level and trend). The coefficients of both the level and trend variables are significant with regard to the various measures of $S_t$, $H_t$ and $D_t$ (except for $D_{c,t}$). This evidence of structural breaks means that banks indeed changed their behaviour due to the influence of the crisis.
5.3 Feedback effects

This section assesses the other side of the endogeneity, i.e. whether banks’ behaviour has feedback effects on the financial sector. This is done first by estimating single equation models and then by estimating a vector error correction model (VECM).

In the single equation model, we test whether $S_t$, $H_t$ and $D_t$ have explanatory power to stress in the financial sector, additional to market-wide shocks. The same variables for market-wide stress ($Mar$, represented by VIX and credit spreads) and financial sector stress ($Fin$, represented by CDS and Euribor spreads) are used as in section 6.1. It is assumed that CDS and interbank spreads include the effects of behavioural interactions within the financial system. To test whether these effects can be explained by $S_t$, $H_t$ and $D_t$, two equations are estimated:

$$
Fin_t = \alpha + \beta Mar_t + \gamma S_t + \delta H_t + \eta D_t + \varepsilon_t \tag{14}
$$

$$
Fin_t = \alpha + \beta Mar_t + \gamma (Mar_{t-1} \times S_t) + \delta (Mar_{t-1} \times H_t) + \eta (Mar_{t-1} \times D_t) + \varepsilon_t \tag{15}
$$

$S_t$ is represented by $S_{r,t}$, $H_t$ by $H_{b,t}$ and $D_t$ by $D_{c,t}$. The selection of these sub-variables is based on the correlation coefficients in Table 3, of which we choose the sub-variables that have the highest correlation with the financial sector variables $Fin$, (CDS and Euribor spreads) and the lowest correlation with the market-wide variables $Mar$, (VIX and credit spreads). The equations are estimated with monthly data of the 2003m10–2009m3 period, with the financial sector and market variables in logs and the behavioural indicators $S_t$, $H_t$ and $D_t$ in terms of 3 months moving averages. This includes lags of $S_t$, $H_t$ and $D_t$ and reduces possible problems of endogeneity. The log levels of the financial sector and market variables are non-stationary, but co-integrated, implying that the equations specify the long term relationship between both series. Equation 14 and 15 assume that deviations between market wide developments and stress in the financial sector are explained by banks’ behaviour. The significance of this is tested in equation 14 by including the variables for behaviour additively, and in equation 15 by adding them in multiplicative form. The coefficients $\gamma$, $\delta$ and $\eta$ of the interaction terms in equation 15 show the effect of market indicator changes with banks’ reactions (measured by $S_t$, $H_t$ and $D_t$). Since the covariance between $S_t$, $H_t$ and $D_t$ is low, multicollinearity is not a problem in the equations.\(^{13}\)

\(^{12}\) By constructing $S_t$, $H_t$ and $D_t$ with the data of our sample, it is implicitly assumed that the pattern of reactions by Dutch banks is typical for the global banking system and that these reaction patterns influence global market prices.

\(^{13}\) The univariate correlations between $S_{r,t}$, $H_{b,t}$ and $D_{c,t}$ ranges from -0.17 to 0.25 (which is not significant at a 5% confidence level).
The regression results in Tables D.1 and D.2 in Annex 4 show that the behavioural variables have additional explanatory power for financial sector stress. The size and dependency variables are equally significant in most of the model equations (and more so than the herding measure), while the R² increases approximately 5 to 10 basis points when St, Ht and Dt are included. This rather limited contribution of the behavioural variables probably reflects that stress caused by banks’ behaviour is to some extent already captured in the market-wide indicators. Another explanation is that the influence of behavioural responses on market prices is partly hidden due to the low (monthly) frequency of our dataset (a well known limitation of balance sheet data).

We also estimate a multi equation model to test the contribution of the behavioural measures to financial sector stress. The following vector error correction model (VECM) is specified,

\[ \Delta Z_t = \Gamma(L) \Delta Z_{t-1} + \Pi Z_{t-1} + \mu + \varepsilon_t \]  

(16)

with vector \( Z_t = (Mar_t, Fin_t, S_{r,t}, H_{b,t}, D_{c,t}) \). Matrix \( \Pi \) contains information on the long term relations between the variables in vector \( Z_t \), the number of it being determined by the Johansen cointegration test. \( \mu \) is a vector of constants. Matrix \( \Gamma(L) \) is:

\[
\begin{pmatrix}
B_{Mar,Mar}(L) & B_{Mar,Fin}(L) & B_{Mar,S}(L) & B_{Mar,H}(L) & B_{Mar,D}(L) \\
B_{Fin,Mar}(L) & B_{Fin,Fin}(L) & B_{Fin,S}(L) & B_{Fin,H}(L) & B_{Fin,D}(L) \\
B_{S,Mar}(L) & B_{S,Fin}(L) & B_{S,S}(L) & B_{S,H}(L) & B_{S,D}(L) \\
B_{H,Mar}(L) & B_{H,Fin}(L) & B_{H,S}(L) & B_{H,H}(L) & B_{H,D}(L) \\
B_{D,Mar}(L) & B_{D,Fin}(L) & B_{D,S}(L) & B_{D,H}(L) & B_{D,D}(L)
\end{pmatrix}
\]

with \( L \) the lag operator (the model includes 2 lags and \( B_{ij} \) the estimated parameters. If \( B_{S,Fin}(L) \), \( B_{H,Fin}(L) \) and/or \( B_{D,Fin}(L) \) are significant, the behavioural measures contribute to explain changes in the financial sector variables (\( Fin_t \)), additional to market developments (since the market-wide variables \( Mar_t \) act as control variables in each equation). The significance of the behavioural measures is investigated by block exogeneity tests. This is a multivariate application of the Granger test (see for instance Enders, 1995). The following restrictions on the behavioural parameters are tested (for \( S_{r,t}, H_{b,t} \) and \( D_{c,t} \)),

14 The signs of the coefficients are inconclusive since the data series both include a boom (in which increases of \( H_t \) and \( D_t \) may contribute to diminishing market stress) and a bust (in which increases of \( H_t \) and \( D_t \) may contribute to rising market stress).

15 Based on the Johansen cointegration test, the model is estimated with 3 cointegration relationships. In these equations a constant is included. The financial sector and market variables are included in logs and the behavioural indicators \( S_t, H_t \) and \( D_t \) in terms of 3 months moving averages.

16 The Akaike information criterion and Schwartz information criterion indicate that 2 lags are more appropriate than 1 lag, while the data sample is too restricted to include more lags.
If the first (second, third) restriction is rejected then the size (herding, dependency) measures add to explain developments in the financial sector. If all three restrictions are rejected, then the financial sector variables significantly relate to the behavioural measures.

The estimation results in Table E in Annex 5 indicate that the restrictions are rejected in the case of the $\text{Fin}_t$ variable CDS spreads for $S_t$, and $H_{bt}$ (5% confidence level) and in the case of the $\text{Fin}_t$ variable Euribor spreads for $H_{bt}$ (5% confidence level). This indicates Granger-causality, running from banks’ behaviour to developments in the financial sector. To conclude, tests based on both single equation and on multi equation models indicate that the behavioural variables have additional explanatory power for financial sector stress.

6 Conclusion

The behaviour of banks can be described by rather simple metrics constructed from firm-specific balance sheet data. Although they are descriptive in nature, the measures identify trends in banks’ behaviour that may lead to the accumulation of financial imbalances. We apply measures of size and the number of extreme balance sheet adjustments to gauge the time dimension of macro-prudential risk, and indicators for the dependency and concentration of reactions to assess the cross-sectoral dimension. Being based on common liquidity exposures across institutions, the measures address a main shortcoming in analytical tools that focus on cross-sectional exposures and pro-cyclicality. Applied to Dutch banks, the measures show that the number, size and similarity of responses substantially changed in the crisis, on certain market segments in particular. They also indicate that the nature of banks’ behaviour is asymmetric; being more intense in busts than in booms. Furthermore, in the crisis the deleveraging of large banks started earlier, was more intense and more advanced than the deleveraging of smaller banks. Statistical tests on the empirical measures, based on regression analyses, confirm that behavioural responses of banks have additional explanatory power to financial sector stress. Given these findings, the empirical metrics are useful for macro prudential analysis, for instance with regard to monitoring frameworks and financial stability models. A better understanding of banks’ behaviour can help to improve the micro foundations of such models, especially with regard to the behavioural assumptions of heterogeneous institutions. The results of our study are also relevant to understand the role of banks in monetary transmission and to assess the potential demand for central bank finance in stress situations.
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Annex 1

Figure B.1 Relative size: claims on central bank
Size measure (Sr), 6 mth mov aver.

Figure B.2 Relative size: bond holdings
Size measure (Sr), 6 mth mov aver.

Figure B.3 Relative size: unsecured wholesale lending
Size measure (Sr), 6 mth mov aver.

Figure B.4 Relative size: retail lending
Size measure (Sr), 6 mth mov aver.

Figure B.5 Relative size: secured wholesale lending
Size measure (Sr), 6 mth mov aver.

Figure B.6 Relative size: equity holdings
Size measure (Sr), 6 mth mov aver.

Figure B.7 Relative size: borrowings from central bank
Size measure (Sr), 6 mth mov aver.

Figure B.8 Relative size: debt securities issued
Size measure (Sr), 6 mth mov aver.

Figure B.9 Relative size: fixed term wholesale deposits
Size measure (Sr), 6 mth mov aver.

Figure B.10 Relative size: fixed term retail deposits
Size measure (Sr), 6 mth mov aver.

Figure B.11 Relative size: secured repo borrowing
Size measure (Sr), 6 mth mov aver.

Figure B.12 Relative size: off balance sheets items
Size measure (Sr), 6 mth mov aver.

Figure B.13 Relative size: wholesale demand deposits
Size measure (Sr), 6 mth mov aver.

Figure B.14 Relative size: retail demand deposits
Size measure (Sr), 6 mth mov aver.
Figure C.1 Crowded trades: claims on central bank
C(i) indicator, 6 mth mov. av.

Figure C.2 Crowded trades: bond holdings
C(i) indicator, 6 mth mov. av.

Figure C.3 Crowded trades: unsecured wholesale lending
C(i) indicator, 6 mth mov. av.

Figure C.4 Crowded trades: retail lending
C(i) indicator, 6 mth mov. av.

Figure C.5 Crowded trades: secured wholesale lending
C(i) indicator, 6 mth mov. av.

Figure C.6 Crowded trades: equity holdings
C(i) indicator, 6 mth mov. av.

Figure C.7 Crowded trades: borrowings from central bank
C(i) indicator, 6 mth mov. av.

Figure C.8 Crowded trades: debt securities issued
C(i) indicator, 6 mth mov. av.

Figure C.9 Crowded trades: fixed term wholesale deposits
C(i) indicator, 6 mth mov. av.

Figure C.10 Crowded trades: fixed term retail deposits
C(i) indicator, 6 mth mov. av.

Figure C.11 Crowded trades: secured repo borrowing
C(i) indicator, 6 mth mov. av.

Figure C.12 Crowded trades: off balance sheets items
C(i) indicator, 6 mth mov. av.

Figure C.13 Crowded trades: wholesale demand deposits
C(i) indicator, 6 mth mov. av.

Figure C.14 Crowded trades: retail demand deposits
C(i) indicator, 6 mth mov. av.
Annex 3

Figure D.1 Number of banks reacting: claims on central bank
Herding indicator $H$ (5% threshold, 6 mth mov. av.)

Figure D.2 Number of banks reacting: bond holdings
Herding indicator $H$ (5% threshold, 6 mth mov. av.)

Figure D.3 Number of banks reacting: unsecured wholesale lending
Herding indicator $H$ (5% threshold, 6 mth mov. av.)

Figure D.4 Number of banks reacting: retail lending
Herding indicator $H$ (5% threshold, 6 mth mov. av.)

Figure D.5 Number of banks reacting: secured wholesale lending
Herding indicator $H$ (5% threshold, 6 mth mov. av.)

Figure D.6 Number of banks reacting: equity holdings
Herding indicator $H$ (5% threshold, 6 mth mov. av.)

Figure D.7 Number of banks reacting: borrowings from central bank
Herding indicator $H$ (5% threshold, 6 mth mov. av.)

Figure D.8 Number of banks reacting: debt securities issued
Herding indicator $H$ (5% threshold, 6 mth mov. av.)

Figure D.9 Number of banks reacting: fixed term wholesale deposits
Herding indicator $H$ (5% threshold, 6 mth mov. av.)

Figure D.10 Number of banks reacting: fixed retail deposits
Herding indicator $H$ (5% threshold, 6 mth mov. av.)

Figure D.11 Number of banks reacting: secured repo borrowing
Herding indicator $H$ (5% threshold, 6 mth mov. av.)

Figure D.12 Number of banks reacting: off balance sheets items
Herding indicator $H$ (5% threshold, 6 mth mov. av.)

Figure D.13 Number of banks reacting: wholesale demand deposits
Herding indicator $H$ (5% threshold, 6 mth mov. av.)

Figure D.14 Number of banks reacting: retail demand deposits
Herding indicator $H$ (5% threshold, 6 mth mov. av.)
### Annex 4

**Table D.1** Behavioural indicators explaining CDS and Euribor spreads (equation 14, additively included)

Based on 66 monthly observations (p values between brackets)

<table>
<thead>
<tr>
<th></th>
<th>CDS 1</th>
<th>CDS 2</th>
<th>CDS 3</th>
<th>CDS 4</th>
<th>Euribor 5</th>
<th>Euribor 6</th>
<th>Euribor 7</th>
<th>Euribor 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX</td>
<td>2.4***</td>
<td>2.0***</td>
<td>2.2***</td>
<td>2.5***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Credit spread</td>
<td>2.5***</td>
<td>2.1***</td>
<td>(0.00)</td>
<td></td>
<td>2.5***</td>
<td>1.6***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sr</td>
<td>-9.9***</td>
<td>0.82</td>
<td>-25.7***</td>
<td></td>
<td>-15.2**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.75)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.02)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hb</td>
<td>0.0</td>
<td>0.1***</td>
<td>0.0</td>
<td>0.0**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.60)</td>
<td>(0.00)</td>
<td>(0.49)</td>
<td>(0.05)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dcor</td>
<td>1.4</td>
<td>0.7</td>
<td>4.2*</td>
<td>3.6*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.27)</td>
<td>(0.49)</td>
<td>(0.05)</td>
<td>(0.07)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-2.8***</td>
<td>-0.63**</td>
<td>-2.5***</td>
<td>-0.9</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.02)</td>
<td>(0.00)</td>
<td>(0.22)</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>R squared adj</td>
<td>0.89</td>
<td>0.91</td>
<td>0.87</td>
<td>0.95</td>
<td>0.76</td>
<td>0.84</td>
<td>0.81</td>
<td>0.87</td>
</tr>
</tbody>
</table>

***, **, * significant at 1%, 5%, 10% confidence level

---

**Table D.2** Behavioural indicators explaining CDS and Euribor spreads (equation 15, multiplicatively included)

Based on 66 monthly observations (p values between brackets)

<table>
<thead>
<tr>
<th></th>
<th>CDS 1</th>
<th>CDS 2</th>
<th>CDS 3</th>
<th>CDS 4</th>
<th>Euribor 5</th>
<th>Euribor 6</th>
<th>Euribor 7</th>
<th>Euribor 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX</td>
<td>2.4***</td>
<td>1.7***</td>
<td>2.2***</td>
<td>0.7**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.06)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Credit spread</td>
<td>2.5***</td>
<td>2.1***</td>
<td>(0.00)</td>
<td></td>
<td>2.5***</td>
<td>1.9**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.06)</td>
<td>(0.00)</td>
<td>(0.04)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market * Sr</td>
<td>-2.7***</td>
<td>-0.5</td>
<td>-6.2***</td>
<td></td>
<td>-8.5**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.87)</td>
<td>(0.04)</td>
<td>(0.23)</td>
<td>(0.71)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market * Hb</td>
<td>0</td>
<td>0.03***</td>
<td>0.0</td>
<td>0.0**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.16)</td>
<td>(0.00)</td>
<td>(0.12)</td>
<td>(0.71)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market * Dcor</td>
<td>0.9**</td>
<td>1.3</td>
<td>2.0***</td>
<td>3.2*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.18)</td>
<td>(0.00)</td>
<td>(0.07)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-2.3***</td>
<td>-1.3***</td>
<td>-2.3***</td>
<td>-1.4**</td>
<td>-0.8</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.03)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R squared adj</td>
<td>0.89</td>
<td>0.92</td>
<td>0.87</td>
<td>0.91</td>
<td>0.76</td>
<td>0.85</td>
<td>0.81</td>
<td>0.82</td>
</tr>
</tbody>
</table>

***, **, * significant at 1%, 5%, 10% confidence level
Annex 5

**Table E, Bock exogeneity test**
VECM specified with 2 monthly lags and 6 cointegration vectors, sample period 2003m10-2009m3

<table>
<thead>
<tr>
<th>Explanatory variable (H0: coefficients of lags equal to 0)</th>
<th>VIX</th>
<th>Credit spr</th>
<th>CDS spr</th>
<th>Eurib. spr</th>
<th>Size S&lt;sub&gt;r&lt;/sub&gt;</th>
<th>Herding H&lt;sub&gt;b&lt;/sub&gt;</th>
<th>Dependency D&lt;sub&gt;c&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mar&lt;sub&gt;t&lt;/sub&gt; VIX</td>
<td>0.10</td>
<td>0.37</td>
<td>0.30</td>
<td>0.36</td>
<td>0.00***</td>
<td>0.64</td>
<td></td>
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<tr>
<td>Credit spread</td>
<td>0.49</td>
<td>0.01***</td>
<td>0.46</td>
<td>0.02**</td>
<td>0.04**</td>
<td>0.68</td>
<td></td>
</tr>
<tr>
<td>Fin&lt;sub&gt;t&lt;/sub&gt; CDS spread</td>
<td>0.58</td>
<td>0.01**</td>
<td>0.06</td>
<td>0.03**</td>
<td>0.04**</td>
<td>0.19</td>
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<tr>
<td>Euribor spr</td>
<td>0.44</td>
<td>0.34</td>
<td>0.01**</td>
<td>0.56</td>
<td>0.01**</td>
<td>0.55</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Behaviour&lt;sub&gt;r&lt;/sub&gt;</th>
<th>S&lt;sub&gt;r&lt;/sub&gt;</th>
<th>0.12</th>
<th>0.45</th>
<th>0.23</th>
<th>0.15</th>
<th>0.06**</th>
<th>0.91</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>H&lt;sub&gt;b&lt;/sub&gt;</td>
<td>0.72</td>
<td>0.96</td>
<td>0.40</td>
<td>0.97</td>
<td>0.00***</td>
<td>0.06**</td>
</tr>
<tr>
<td></td>
<td>D&lt;sub&gt;c&lt;/sub&gt;</td>
<td>0.00***</td>
<td>0.10</td>
<td>0.20</td>
<td>0.94</td>
<td>0.61</td>
<td>0.00***</td>
</tr>
</tbody>
</table>

Rejected restriction
Sr ->CDS
H<sub>b</sub> ->CDS
H<sub>b</sub> ->Eurib

P-values Wald tests, ***, **, * H0 rejected at 1%, 5%, 10% confidence level
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