Stress Testing Linkages between Banks in the Netherlands

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STRESS TESTING LINKAGES BETWEEN BANKS IN THE NETHERLANDS

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Abstract

Assessing the stability of the financial sector is becoming more common in many countries. This paper presents two useful approaches, applied to the Netherlands. First we discuss the results of a contagion analysis of the Dutch interbank market. We use various ways to measure linkages between banks and find that the interbank market is fairly robust. We then turn to a network analysis of payment flows between Dutch banks. This analysis provides us with a better understanding of the network structure in this type of market. We specifically look at the effect of the recent turmoil on the payment network and find no significant changes.

JEL codes: G1, G2, E5
Key words: interbank, payment, systemic risk, financial stability, network, topology

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CHAPTER 11
STRESS TESTING LINKAGES BETWEEN BANKS IN THE NETHERLANDS

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Contents

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1. Introduction

Assessing the stability of the financial sector is well-established in the Netherlands. Spurred by the IMF's Financial Sector Assessment Program (FSAP) in 2004 and by increased attention for financial stability, as witnessed by the creation of a separate financial stability division at the central bank (De Nederlandsche Bank), a number of analyses have been conducted. An example is the partial analysis conducted and reported in the bi-annual Overview of Financial Stability in the Netherlands, highlighting *inter alia* operational problems in payment systems or the effect of credit risk transfer on the soundness of financial firms. Sometimes such analyses come eerily close to reality as is the case with the securitization scenario computed in mid 2007.[2] In this scenario banks were asked to compute the cost of taking their most recent securitization back on the book. Liquidity effects found in this scenario were limited because of the short time horizon considered. In reality, in the late summer of 2007, the vulnerability of banks for the so-called originate-to-distribute model, in which banks securitize issued loans and sell them to interested investors via special legal entities, emerged. Rising subprime mortgage default rates led to widespread downgrading of structured credit products containing such loans, inducing growing doubts about the nature and value of the assets of special legal entities. This again caused the market-financing of these entities to evaporate, generating uncertainties about possible draw-downs of credit lines at sponsor banks. Indeed, some banks had to take the securitized loans back on their balance sheets. Also markets for other structured credit products dried up, contributing to the uncertainty about losses. Internationally, many banks were confronted with these effects, putting their liquidity and solvency positions under pressure.

Another example is the ongoing analysis of Dutch banks as operating in a network; this will be the focus of the current chapter. In this type of analysis we study interrelationships between participating banks. Naturally, understanding the risks in individual institutions is important as well, but this is not the focal point here. We will discuss two related examples of such analyses: the interbank loan market and the interbank large value payments system.

The first analysis considers the contagion effects of bank defaults in the interbank market. In this market banks buy and sell (liquid) funds which are largely unsecured and of short term nature. Given the large notional volumes even small probabilities of default would introduce considerable (credit) risk into the system. Using various methods the linkages between banks are estimated. Given a matrix of the linkages, each of the banks is toppled in turn. Given this failure, the impact on other banks and the banking system as a whole is analyzed. For instance, the number and type of banks that fail following the first bankruptcy is measured, as well as the losses in terms of total assets.

In the second type of analysis the network topology of large value payments between Dutch banks in the TARGET system is considered. We will briefly discuss the various network measures available and then turn to a sensitivity analysis. We will for example remove some of the banks (nodes) from the network and see how this affects the structure of the remaining network.

The set up of this chapter is straightforward. We first provide a brief overview of the Dutch banking sector as a background to the next two sections. These sections will, in turn, discuss the interbank loan market and the interbank payments network. Finally, we conclude and discuss the results of these two interrelated analyses.

2. The Dutch financial landscape

The final decades of the twentieth century saw a distinct change in the Dutch financial landscape. Globalisation, conglomeration, the blurring of distinctions between banking, insurance and securities activities, the single market for financial services in the European Union, and the birth of the euro are changing the arena. The liberalisation of capital markets in the Netherlands in the 1980s had eliminated restrictions on the cross-border activities of financial institutions. Subsequent developments in information and communication technology made these activities economically profitable. However, in order to be successful players in a global financial market, the banks in the Netherlands had to realise economies of scope and scale, first nationally and then internationally. Growth was stimulated by the abolishment in 1990 of the ban on banking-insurance mergers, paving the way for the creation of large financial conglomerates. Immediately after the prohibition was lifted, a process of mergers and acquisitions ensued (van der Zwet (2003)). In fact, the Netherlands was one of the

[2] See DNB (2008).

pioneers in the area of 'Bancassurance'.[3] Growth was not only realised cross-sector but also cross-border by expanding international activities.

The banking sector is important for the Netherlands. Total banking sector assets are almost six times GDP, and this ratio is among the highest in Europe. In terms of Tier 1 equity, the largest Dutch banks also feature in the top 25 of the world. In addition, the banking sector in the Netherlands is very concentrated. The largest three banks hold three quarters of total savings and deposits. Other measures of bank activity, like total assets or income show similar results. Nevertheless competition in especially the residential mortgage market is intense.

Dutch banks are relatively internationally oriented. About two-fifth of total assets are held in foreign countries, while already more than 50% of the consolidated income is earned outside the Netherlands.

The fact that the market is concentrated and firms are large, implies first of all that prudential concerns very quickly turn into financial stability concerns. This has a number of consequences. First of all, given the blurring of distinctions between financial sectors and products in the Netherlands since 1990, it was obvious that more co-operation was needed between the supervisors in the Netherlands, both in the area of prudential supervision and in that of conduct-of-business supervision. An important reason for co-operation in the area of prudential supervision is that sectoral regulation might fail to capture the risk characteristics of a financial conglomerate as a whole. Financial conglomerates also call for a consolidation of prudential supervision. Moreover, the increase in the number of financial conglomerates has been accompanied by a blurring of the boundaries between traditionally distinct products. A common example in the Netherlands is a mortgage combined with a unit-linked life insurance policy; this hybrid financial product embodies banking, securities and insurance components. Since different types of financial institutions can offer these complex financial products, they call for a harmonisation of the prudential treatment. Such a harmonised approach safeguards the level playing field. Similarly, adequate conduct-of-business supervision requires that for similar products and markets a similar regime is applicable, regardless of the sector of the supplier.

Secondly, especially in a highly concentrated banking system as that in the Netherlands, it is difficult to draw a line, in practice, between the responsibility for systemic stability, including the function of lender of last resort, and that for prudential supervision. Recent experiences have shown that this is an issue in other countries as well. Moreover, it is no coincidence that with the development of new, complicated

[3] The bankassurance model has received mixed support. In earlier years firms like Citigroup expanded across sectors while recently there seems to be a trend to roll back such diversifying acquisitions. See Van Lelyveld and Knot (2008) for an analysis of the value effect of cross-sectoral conglomeralistation.

products and the intensification of cross-sector and cross-border linkages, the attention for financial stability issues and the interplay between macro- and micro-prudential risks has increased. The choice in the Netherlands to maintain a structure in which the central bank is also responsible for the prudential supervision of banks,[4] has to do with financial stability considerations. In view of the high degree of concentration of the banking sector, systemic and prudential supervision are appropriately placed within the central bank.

3. Interbank loan market

3.1 Review of the literature

There is a small but growing body of literature modelling the interbank loan market using similar approaches. Basically the approach consists of taking the matrix of all bilateral exposures between banks and then letting one (or more) banks default, either randomly or dependent on a model which assesses banks´ sensitivity to some (market) risk. Authors have, mainly driven by data availability, taken various approaches to determining the matrix. A good review is for instance provided by Upper, Christian (2007); this section will therefore only provide a concise summary.5

The analysis of the structure of the interbank loan market as a source of financial sector contagion is of a relatively recent date. Theory discerns both direct and indirect contagion (De Bandt and Hartmann (2001)), based on the type of linkages between institutions. Direct contagion results from direct (financial) linkages between banks, such as credit exposures. Indirect contagion is the result of expectations about a bank's health and about the resilience of the sector, given developments at another bank. The exposure of banks to similar events, such as asset price fluctuations, does not create a direct link between banks and hence cannot result in direct contagion. Although these two contagion channels can work separately, direct contagion and indirect contagion are obviously not mutually exclusive and may even reinforce each other. For instance, a bank failure may lead to further bank failures through direct linkages and may induce further bankruptcies if depositors *assume* the existence of linkages between banks (regardless whether these assumptions are true or not). In this section, we focus on direct linkages –or direct contagion– between banks.

In the literature it has become clear that the structure of the interbank loan market is of crucial importance for contagion. It determines the impact of a shock to an individual bank on the entire system of banks. Allen and Gale (2000) distinguish three

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[4] DNB is also responsible for the prudential supervision of insurance companies and pension funds. The Authority Financial Markets (AFM) is responsible for conduct-of-business supervision.

[5] This section builds on van Lelyveld and Liedorp (2006).

types of interbank market structures. First, they define a complete structure as one where banks are symmetrically linked to all other banks in the system. Secondly, an incomplete market structure exists when banks are only linked to neighbouring banks. A special case of this structure is introduced by Freixas, et al. (2000): the money centre structure. In this structure, the money centre bank is linked symmetrically to the other banks, while the latter have no links among themselves. Thirdly, an incomplete market structure is defined as one where two or more separate (but internally connected) markets exist simultaneously. Because of diversification effects a complete market structure may give the highest level of insurance against an unexpected liquidity shock hitting an individual bank. However, such a structure might also propagate shocks more easily through the system of banks, as shocks will not remain isolated at one bank or at a cluster of banks.

Empirical studies that try to model the structure of the interbank market and (the impact of) contagion risks have been carried out for several countries. These studies include Elsinger, et al. (2006), Degryse and Nguyen (2007), Upper and Worms (2004), Van Lelyveld and Liedorp (2006), Mistrulli (2007), Blåvarg and Nimander (2002), and Wells (2002) to mention just a few. Most of these studies use balance sheet data or large exposures data as proxies to determine the interbank market structure. Blåvarg and Nimander (2002) and Mistrulli (2007) use reported bilateral data to model contagion risk. Mistrulli (2007) concludes for the Italian case that estimates based on aggregate data may underestimate contagion risk.[6] Mueller (2006) explores the Swiss interbank market using data from the Swiss national bank. Applying network analysis[7], she discerns systemically important banks and possible contagion paths. Furfine (1999) estimates contagion risk in the US interbank market, but uses bilateral data from the payments system Fedwire to build the interbank market structure. The majority of these studies finds that contagion effects are small, especially since high loss rates are rare.

The study described below relates to these studies in several ways. For one, we based our analysis on balance sheet data and large exposures data as well. Furthermore, we used different loss rates to test the strength of the system under different shocks. However, we add a second model variant in which we incorporated the input of banks themselves with respect to their bilateral exposures. This provides the opportunity to

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[6] However, this conclusion is based on a comparison of the results using on the one hand maximum entropy (banks´ exposures are evenly spread over all other banks in the system) and on the other hand the reported bilateral exposure data. Given the presence of a money centre bank structure in the Italian interbank market, it is clear that the assumption of maximum entropy, or maximum spread, becomes less appropriate.

[7] Measuring for example the number and size of interbank linkages, the distance from other banks, the importance of counterparts and the position in the network. See also the second part of this chapter which discusses a similar approach applied to the Netherlands.

test the usefulness of the large exposures data for estimating the interbank market structure.

3.2 Data description

As is common in this type of approach (Upper and Christian (2007)), we first constructed a matrix of interbank exposures. The structure of interbank linkages between N banks would then be fully represented by this NxN matrix of exposures (see X in Figure 1). The columns represent banks´ lending while the rows represent banks´ borrowing. Hence, the matrix elements x_{ij} in Figure 1 represent the liabilities of bank i towards bank j. The row and column totals (i.e. each bank's total interbank lending and borrowing, a_j and l_i) are known. Clearly, a bank does not lend to itself: the cells on the main diagonal from upper left to bottom right are all zeros.[8]

Figure 1: The interbank lending matrix

$$
\begin{array}{c|c}
X = \begin{pmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1N} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{iN} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ x_{N1} & \cdots & x_{Nj} & \cdots & x_{NN} \end{pmatrix} & \begin{matrix} \Sigma_j \\ l_1 \\ \vdots \\ l_i \\ \vdots \\ l_N \end{matrix} \\ \hline
\Sigma_i \quad a_1 \cdots a_j \cdots a_N &
\end{array}
$$

Source: Upper and Worms (2002)

In the Netherlands it is difficult to estimate the cells of the matrix, as there is no credit register providing bilateral exposures. An often used alternative source of information is the large exposures reporting. Based on such reports and using the assumption that the distribution of large exposures over interbank counterparties is the same as in the interbank market itself, we can estimate a lending matrix using the RAS algorithm.[9] A specific contribution of our study was to compare the outcomes based on the large exposure data to the outcomes based on data requested specifically from the ten largest institutions. The concentrated nature of the Dutch banking sector, as

[8] Moreover, not all banks need to be both a lender and a borrower at the same time. In fact, a bank need not be active in the interbank market at all.

[9] Blien and Graef (1997).

described earlier, assures coverage of over 90% of total assets.[10] Given these two data sources, we constructed two matrices and used these for our scenario analysis as described in the next section.

3.3 Scenario analysis

Our basic approach is to assume that one of the participating banks suddenly defaults and that consequently (part of) the exposures on this particular bank become worthless in the event. If the exposure of another bank to this failed bank is larger than its tier 1 capital, this second bank defaults as well (we call this the first round). Then, if the combined exposure of another bank to these two, or more, failed banks is again larger than its tier 1 capital, the bank also defaults (we call this the second round). This process continues till no additional banks default. In this way the default at one bank could lead to a contagious series of defaults at other banks. As there are no reliable data on the loss rate in case of default, we vary over several loss rates (25%, 50%, 75% and 100%). For each individual bank there is a scenario in which it suddenly defaults. Alternatively, there are scenarios in which (geographical) groups of banks initially default.

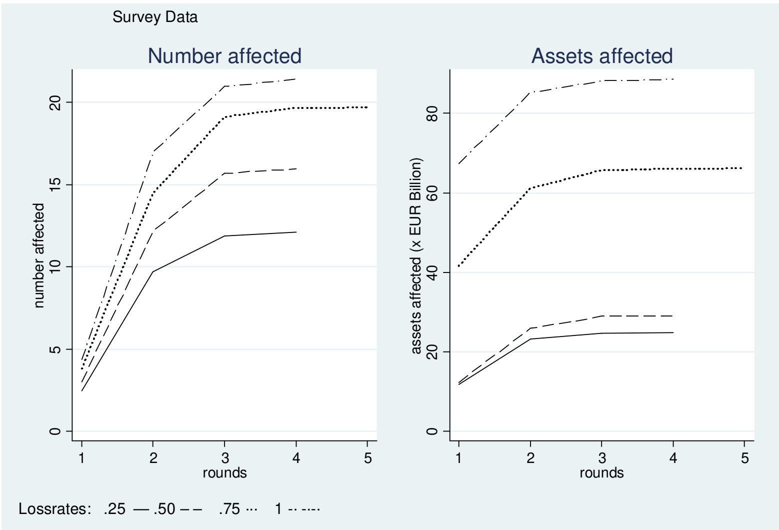
Completely idiosyncratic shocks are rare and thus our assumption of a single bank failure due to some exogenous shock might be a relatively strong one. It seems more likely that several banks will be simultaneously affected in case of a shock. Moreover, bankruptcy is often preceded by a period of distress and thus other banks are able to take measures in time. In contrast, the nature of operational risk events is different as exemplified by the Barings case. There, activities of a single trader led to the demise of the entire bank. In this case, the factor that triggered the failure was idiosyncratic to Barings bank, and other banks were not directly influenced by this shock. Further, such a severe scenario analysis may be useful in determining the sequence and path of possible contagion. Modelling the probability of default conditional on the state of the economy and/or crisis would be a possible future improvement (Elsinger, et al. (2006)).

We will not present the full analysis here but provide a flavour of the type of analysis conducted and then turn to the conclusions in the next section. As described earlier, we use the large exposure data and the survey data. The scenario analysis gives us a distribution of possible outcomes. The left panel of Figure 2 shows the mean of the distribution of the cumulative number of failed banks per round and per loss rate (based on the large exposures data), while the right panel shows the mean of the cumulative

[10] For the banks not included in the sample (i.e. the smaller banks) we assumed that bilateral exposures would be distributed according to maximum entropy. We also estimated a maximum entropy matrix without any prior information whatsoever (Not presented here. See Van Lelyveld and Liedorp (2006)).

assets of these failed banks per round and per loss rate.[11] Note that "assets affected" is defined as the total assets of the failed banks. A bank may suffer losses following a bankruptcy, but these losses are not included in the measure of assets affected if it does not fail consequently. However, every loss does make the respective bank more vulnerable to subsequent losses in future rounds. For both panes the cumulative effects obviously increase when the loss rate is increased. In case we use a 75% loss rate however, the contagion path lasts longer, as there are more rounds compared to the use of other loss rates. With a higher loss rate (100%), the failure of all banks that can be affected already have been triggered in an earlier stadium of the process, such that all banks that can be affected *are* already affected in previous rounds. Hence, no banks are left to be affected in the higher rounds.

Figure 2: Cumulative Effects of Simulated Failures



Source: Van Lelyveld and Liedorp (2006).

We then compared the results based on the large exposure data with the results using the survey data and find that the large exposure data provide a good approximation to the survey –or real– data. Other measures of interest (not shown here) include the relationship between the size (total assets) of the failing bank and the size of the contagion effects: do bigger banks cause higher distress? Further, we looked at the sensitivity of our outcomes to the use of different loss rates in more detail. Finally, we analysed which geographical region posed the biggest risk to the stability of the Dutch interbank market. This risk measure turns out to be the most relevant for our analysis, as exposures on foreign counterparties in certain geographical regions (specifically Europe or the US) have the largest impact on the Dutch banking sector. These scenarios trigger

[11] The initially defaulting bank is excluded in these measures.

even the failure of one of the large banks in the system and the highest number of banks and the most assets are affected.

3.4 Results

Our analysis showed that the most important risks in the Dutch interbank loan market stem from exposures on foreign counterparties, in particular European and North American counterparties. This result holds regardless of the information source used. The national interbank market only seems to carry systemic risks if a large bank fails, although even in this extreme and unlikely event not all the remaining banks are affected. In fact, none of the large bank failures trigger the failure of another large bank. The Dutch banking system hence cannot be pictured by one single line of dominos and the amounts outstanding per counterparty are relatively small (i.e. losses are limited).

The analysis also showed that the distribution of the exposures in accordance with maximum entropy (maximum dispersion) is not appropriate for estimating bilateral exposures in a concentrated market, such as the Dutch market. In addition, for an accurate assessment of the risks in the interbank market, there is not a clear advantage in using either the large exposures data report or survey data. Both data sources give an adequate and similar overview of the systemic risks in the interbank market. At the individual bank level, however, there are material differences. Working from the premise that the survey data are a more reliable source of information since they have been specially requested, this implies that the large exposures data reports are not well suited for monitoring the individual interbank exposures of a particular bank. However, for estimates of contagion effects at the macro-level, the large exposures data form an appropriate (and easier) data source.

The most important conclusion, based on the research presented, is that in order to make the analyses more informative, information about foreign exposures is necessary. As the largest contagion effect flows outside the domestic market, we do not how this affects the foreign counterparties and what reciprocal effect this may have again on Dutch banks. Other studies in this area suffer from the same issue. In an increasingly integrated market, like the interbank loan market, it might therefore be fruitful to merge the various analyses.

On the whole, our simulations suggest that contagious defaults are unlikely, although we cannot rule them out completely. An important caveat is that we do not model behavioural reactions. Especially in a crisis that is developing over time, it is important to model the reaction of participating banks to market events. Similarly, we did not attach any probabilities to the default of banks.

4. Payment networks[12]

A different perspective on the linkage between banks in the Netherlands is provided by analysing the patterns in payment systems. Here, we focus on the Dutch large value payment system which is operated by the central bank and forms part of the European system for euro denominated payments. In this payments system the participants, mainly banks, transfer large value funds to each other. These payments reflect economic transactions by bank clients (e.g. an employer who transfers wages to employees) or for own account of the banks (e.g. interbank loans). An important difference with the approach discussed in the previous section, is that the information provided by the payments stream is much more ethereal. In the interbank loan market banks are linked as long as a bank has an exposure on another bank. In payment streams the link between banks ceases to exist as soon as the payment is settled. Presently this generally occurs quite rapidly and without recourse.

This section highlights the main aspect of a study into the Dutch payment system. It will first provide a description using conventional measures and then turn to network analysis measures. We will then show how these measures can be used to, for instance, analyse the failure of important banks or to analyse the 2007 sub-prime turmoil.

4.1 Traditional descriptions of payment networks

Traditionally, networks have been described in terms of for instance the volume of transactions, the value transferred or the number of participants and for many purposes this is adequate enough. In terms of these metrics, the Dutch system is an active, medium sized network and thus exemplary for many smaller countries. The numbers in Table 1 show that the European TARGET and U.S. Fedwire systems are both large payment systems of the same order of magnitude. The Dutch large value payment system (Top) is clearly smaller, although the average transaction value is relatively high.

Table 1: Key daily payment characteristics for Top (NL), TARGET (EU), CHAPS (UK) and Fedwire (US).

	Top	***TARGET***	***CHAPS***	***Fedwire***
Participants	155	10,197	NA	6,819
Transactions (x1000)	151 (18.1)	312	116	519
Value (bil €)	151 (173)	1,987	297	1,634

[12] This section draws on Pröpper, et al. (2008).

Trans. value (mil €)	9.9 (9.5)	6.4	2.6	3.1

Source: Top (DNB), Target (ECB bluebook), CHAPS and Fedwire (BIS). The period is 2005 except for TOP where the data are for 6/2005-5/2006. The TOP system is with evening settlement in brackets.

4.2 Network measures

Network analysis, which is of a more recent date, considers not so much the individual banks or nodes, the technical term used for network participants, but the relation between these nodes. In terms of friendships, for instance, the focus would not be so much on the individual but on her relationship with others. How many people does she now and many people do they know? How often does she interact with them? Using what medium? Are friends of her friends, friends as well? Measures have been developed for friendship networks and other types of networks and we will discuss a selected number below (see Box 1).[13]

Box 1 **Network properties**

The most basic network properties are the number of nodes *nodes (n)* and *links (l)* **[14]**. The former is often referred to as the *size* of the system. The relative number of links l to the possible number of links determines the network *connectivity (c)*. Alternatively, it is the probability of two nodes sharing a link. *Reciprocity*, finally, is the fraction of links with a link in the opposite direction. A *path* is an alternating sequence of connected nodes and links that starts and terminates at a node. If all links represent unit length, *path length* l_{ij} between nodes i and j is the length of the shortest path between the nodes. Network *eccentricity (e)* is defined as the largest of the observed path lengths.

The number of links between one node i and other nodes determines the *node degree* (k_i). In a directed network these connections consist of incoming and outgoing links, which respectively determine the *in-degree* ($k_{in,i}$), the *out-degree* ($k_{out,i}$), and *node degree* (k_i) by $k_i = k_{in,i} + k_{out,i}$. Every link contributes exactly one unit to both the out-degree of the node at which it originates and to the in-degree of the node at which it terminates. The *average degree* (k_{avg}) of a network is the relative number of all links to all nodes. The *maximum in-degree* and the *maximum out-degree* are determined the maximum degree values and the maximum deviations (to the upside) from the respective average degree values.

Degree correlations between neighbouring nodes provide additional information on the network structure. In an uncorrelated network the degree of one node is independent of its neighbouring nodes: being popular does not mean you friends are popular as well. Degree correlations therefore provide information on whether nodes are generally connected to nodes with comparable degree, to nodes of different degree, or if there is no relation at all.

Another concept to describe the correlation between nodes is the *clustering coefficient* (C_i), which gives the probability that two neighbours of a node share an undirected link among themselves. It marks the

[13] See Dorogovtsev and Mendes (2003) for an overview of the methods used.

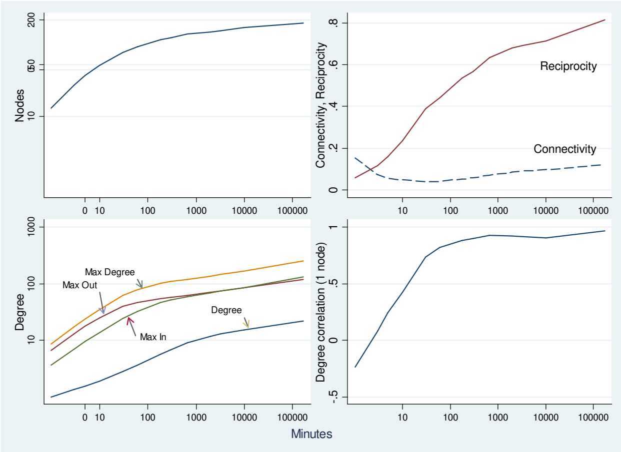
[14] See Dorogovtsev and Mendes (2003) and Soramäki, et al. (2007).

density of connections in the direct neighbourhood of a node (cliquishness). The meaning of the coefficient becomes particularly clear in a social context where it is the extent of the mutual acquaintance of friends. The clustering coefficient ranges from 0 for a tree network to 1 for a completely connected network.

As mentioned above, the time dimension is important in the analysis of payment networks. In a short time span, not many transactions will take place. The number of connections (the degree), or any other measure of being connected, will thus be low as well. As the observation period increases the number of transactions recorded will increase. Typically, network measures are being computed using a one day snapshot of the data. It is not clear, however, that this is the optimal period. In the figure below, we show the development over time (x-axis in minutes of observations) of several important network measures. Note that the x-axis, and in some cases the y-axis as well, is on a logarithmic scale.

Figure 3 shows that major developments take place mostly in the first hour of network formation, consequent growth (up to one day) is more gradual. The *size* of the network (top left) measured 88 ± 6 nodes on an hourly basis and 129 ± 5 nodes on a daily basis. *Connectivity* (top right), the fraction of actual to possible links, provides a better view on the relative growth of nodes and links. This measure shows that the network remains very sparse over all time periods. Connectivity rapidly declines from 0.16 ± 0.12 after one minute to a minimum of 0.04 ± 0.01 after approximately 30 to 60 minutes, to increase thereafter at a lower pace to 0.07 ± 0.00 after one day and 0.12 after 257 days. The explosion of nodes in the first hour suppresses connectivity, because the growth of links does not keep up with the growth of nodes. After one hour, however, the situation reverses. At all times the network keeps its low connectivity and remains far from connected. Even after 257 days 88% of all theoretically possible links have not been used for a single transaction. *Reciprocity*, the fraction of links with a link in the opposite direction, displays a rapid increase in the first hour to on average 0.44 and increases at a lower rate to on average 0.63 after one day. It means if there is a link in one direction a link in the opposite direction is very likely.

Figure 3: Selected network measures



Source: Pröpper, et al. (2008)

4.3 Sensitivity to shocks

Given the description of the network measures, we will now discuss how the network is affected if one (or more) participants are taken out of the system. As we cannot model adaptive behaviour, this is a static exercise. Removing a certain number of nodes will always, no matter the order of taking them out, lead to the same result in the end. The ordering (or path dependence) of taking them out can reveal that certain nodes are particularly important to the system.

In Figure 4, we show the change in a number of measures (y-axis) after the removal of nodes, ordered from the most highly connected node ('-1') to lowly connected nodes. The network becomes smaller and even sparser as, for instance, shown by the *degree* values (top left pane). Further, it increases the path lengths between the remaining nodes. In the removal of the seventh node this phenomenon is outweighed by the accompanying loss of the single link nodes and the shortest paths between them and all other nodes. Specifically, the top right pane shows that *path length* and maximum path length, or *eccentricity*, increase from 2.2 to 2.5 and from 3.3 to 4.2, respectively. The bottom left corner shows that the local structure starts to break down. *Clustering*, or the local density of connections, decreases from 0.40 to 0.23. The removal of nodes two to four has a disproportionately negative impact on clustering in comparison to the other nodes. The *out-out degree correlation* increases more steadily from -0.38 to -0.14 (= loss of correlation).[15] The outcomes for *nearest neighbours* and *second nearest neighbours* confirm this breakdown in structure (bottom right pane).

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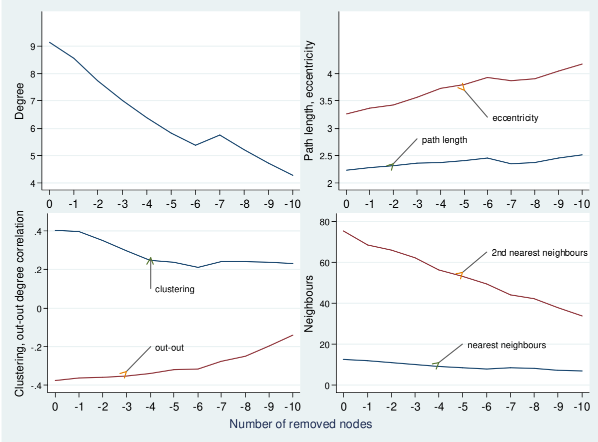
[15] In-in degree correlation increases from -0.38 to -0.10. In-out degree correlation decreases from 0.93 to 0.59.

Figure 4: Impact of node removal on network properties



Source: Pröpper, et al. (2008). The panes show (1) degree, (2) path length and eccentricity, (3) clustering, out-out degree correlation, (4) nearest and second nearest neighbours (z**1** and z2)

The analysis shows that although the Dutch financial sector is quite concentrated, removing important banks does not produce the same cliff effects as would be the case in a typical centre-periphery structure. In such a structure, the removal of a bank in the periphery hardly affects the network, while the removal of the bank in the centre leads to an immediate breakdown of the structure.

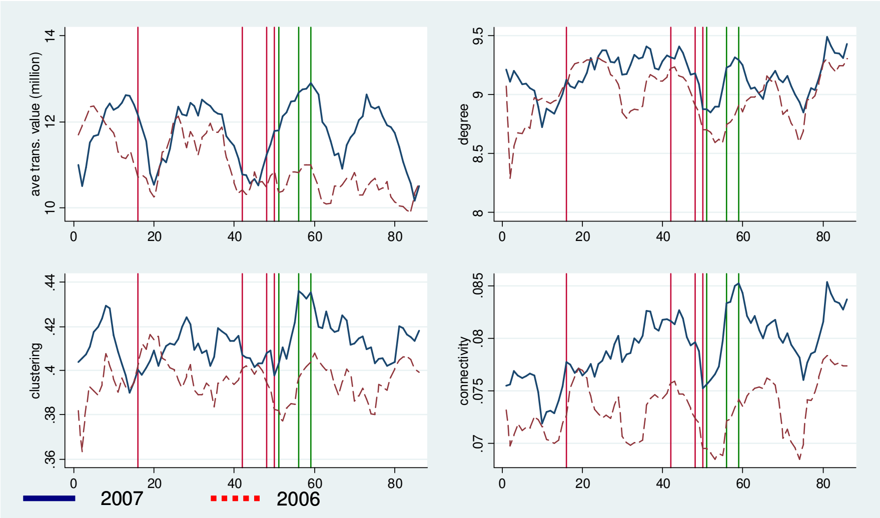
These network measures are also useful to analyse real events in the financial sector, such as the 2007 subprime turmoil (see Box 2).

Box 2 **The market turmoil in 2007**

Network measures can also be useful to look at the effects of the 2007 turmoil on the structure of bank relationships. Some previously liquid credit markets abroad have quickly dried up due to a loss of confidence between counterparties and we might see this reflected in payment patterns in the large value payment system. Payments are, after all, a mere reflection of economic agents' decisions and actions. To analyse whether market turbulence has affected the payments patterns we show selected measures in Figure 5. The dotted (solid) line shows 2006 (2007) data.[16] The vertical lines denote events which we considered negative (red) or positive (green). We conclude that it has not *materially* affected the network structure of the payment system during the investigated period. Severe disruptions in the payment system would inevitably have shown up in the discussed measures. There does seem to be an effect on the level of the measures as the payment activity (not shown here) proved higher during the investigated turmoil period in 2007 than in the corresponding period in 2006. In addition, there does not seem to be an effect related to the positive and negative events.

[16] We have not yet extended this data period due to the computational burden.

Figure 5: Development of a selection of traditional system measures and network properties over time



Source: Pröpper, et al. (2008). The panes are (1) transaction value, (2) degree, (3) clustering, and (4) connectivity. To make the two sets of data comparable we start both series on the same day of the week. Further, we have dropped all days corresponding to Dutch public holidays. The series are 5 day moving averages. A list of the events included is available upon request.

5. Conclusions

This chapter discussed two different approaches to gauge the risks in the Dutch financial markets. First, we analysed the Dutch interbank market, a market where banks extend short term loans to each other. Then we turned our attention to the large value payment system. In the analyses we tried to uncover hidden risks by first unravelling the structure of the market and in particular the way the participants are linked to each other. We then conducted a number of tests to stress the structure. In the case of the interbank market we analysed what would be the result of the default of (groups of) banks. We included second round effects but did not model reactions of market participants. As reliable information on loss rates (given default) is not available, we computed our results subject to a range of loss rates. In the case of Dutch payment system analysis we conducted a thought experiment by removing one by one the most important players. We also looked at the 'natural experiment' the 2007 turmoil in the financial markets has provided us.

The main conclusion that we can draw based on these analyses is that the Dutch financial system is quite stable. For example, to get losses worth worrying about requires quite severe stress events in the interbank market. Furthermore, the system has a relatively straightforward structure. Depending on the cut-off, the three or four biggest banks are the most important in most respects. However, there does not seem to be such a stark division between first and second tier banks as in some other countries. Finally, the analyses turned out to be useful for assessing the stability of the Dutch financial sector.

There are important challenges in this area of research, however. As noted above, we did not model participant reactions. It is for instance likely that if banks observe another bank to be in trouble, they will try to reduce net exposures on the bank in question, either by calling in loans or by borrowing more from the bank. Modelling reaction functions, especially in times of stress, is particularly difficult.[17] A second problem is that data collection is generally organised within countries or regions. Information about exposures generally stays within national jurisdictions. Payment systems may operate across borders but information on individual payments is generally kept within national boundaries. Thus, while financial markets become increasingly intertwined, data collection, and thus our ability to do wide-ranging analyses, is lagging.

[17] A possible avenue could be the use of experimental economics as in Heijmans, et al. (2008).

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