PhD Thesis

Essays in Payment Systems and Financial Stability

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April 2010

Contents

Preface

This PhD thesis was written during my enrolment as a PhD-student at the Department of Economics, University of Copenhagen from September 2006 through April 2010. Thomas Rønde was my supervisor and I thank for all his advice and comments to my work. It has opened by eyes to new insights and improved my research.

I thank my fellow PhD-students at the Department of Economics, Peter Norman Sørensen and Christian Schultz.

Morten Bech has been my secondary supervisor during the PhD-project. I thank him for being an inspiring co-author, for our interesting discussions, and for the visit, he arranged for me in the Federal Reserve Bank of New York in October 2007.

I'm very grateful to Danmarks Nationalbank for the funding of my PhD-project. I thank the staff of the Payment Systems division for giving me insight into the actual workings and ongoing developments of national and international payment and settlement systems. Danmarks Nationalbank has made data available for two of the papers. I thank Mads Kristoffersen, Irene Madsen and Tina Skotte Sørensen in this connection. I have enjoyed the lively atmosphere among my fellow PhD-students in Danmarks Nationalbank; Lars Jul Overby, Jesper Pedersen, Søren Hove Ravn, Allan Sall Tang Andersen, Jannick Damgaard, Claus Bajlum, René Kallestrup and Martin Seneca.

I spend the fall 2008 at Bank of Finland's Research Department. I thank Jouko Vilmunen, Tuomas Takalo, Kari Kemppainen and their colleagues for their hospitality and for welcoming me in their research environment.

Finally, I thank my family and friends for their love and support.

Kirsten Bonde Rørdam
Copenhagen, April 2010

I am very grateful to the members of my committee, Cornelia Holthausen, Carsten Tanggaard and Hans Keiding, for the valuable comments and suggestions made both in their report and at my defence July 9, 2010.

Kirsten Bonde Rørdam
Copenhagen, September 2010

Introduction and summary

This thesis consists of three papers within the field of payment systems and banks' financial stability. The first and second paper relates mostly to payment systems, their functioning and why banks use payment systems to settle transactions. The third paper considers banks' financial stability and how it relates to the composition of their loans.

The first paper entitled *The Topology of Danish Interbank Money Flows* (joint work with Morten L. Bech and published in Banks and Bank Systems, Issue 4, 2009, p. 48-65) explores the first topological analysis of Danish interbank money market flows. A growing literature on the functioning of payments systems has emerged using the network topological approach, see Soramäki et al. (2007) among others.

Banks use large-value payment systems to settle their obligations. Our analysis is therefore based on a data set consisting of all transactions originated over the Danish large-value payment system in 2006. The purpose of these transactions are not registered. The algorithm developed by Furfine (1999) is therefore used to divide the data set into overnight money market transactions and other transactions. The algorithm defines a transaction as an overnight loan if there is a transaction from bank A to bank B on day t and a reverse transaction from B to A on the same amount plus interest on the following day.

We identify two economically different networks. The first network is the money market network, which consists of overnight money market loans. The second is the payments network consisting of all other transactions, primarily the settlement of customer driven transactions and banks' proprietary transactions.

Several findings emerge. First, we find that more banks are active in the payments network than in the money market network. Second, two large commercial banks play a major role in both networks, but somewhat surprising the important bank-pair in the payments network is different from the major bank-pair in the money market. Third, the top-10 banks account for a significant share of the turnover in terms of values in both networks. This is quite natural as large banks tend to be more connected than other banks. This implies that both networks are rather concentrated. Fourth, the average loan size for the top-10 banks is larger in the money market network than in the payments network. Fifth, taking into account that two banks are linked if there is at least one transaction between them, we find that few links exist on each business day.

The activity of the networks are affected by seasonal effects. The payments network extends by the turn of the month and quarter and on the first business day following a holiday. In contrast to this, weekday effects drive the calendar effects observed in the money market.

In the final part of the paper, we consider two different events, a temporaneous stop for the settlement of transactions a) in the large-value payment system and b) for a major bank. These events change the structure of the networks. The money market network widens such that more, but less valuable, overnight loans were granted. The activity of the payments network decreased. Moreover, the second event also caused accumulated settlement demand.

Thus, the results show that the structure of these two networks differs. This is as expected since the types of transactions handled differ across the networks. Furthermore, seasonal effects and temporaneous stops in the settlement process affect the structure of both networks.

The second paper is entitled *Competition from Settlement Banks in RTGS-Systems: The Case of Indirect Settlement* (singleauthored). In this paper, we define settlement of payments within a payment system as *direct settlement*, since a bank submits payments directly to its recipients, and *indirect settlement* as payments submitted via a settlement bank. Other frequently used terms for this phenomenon are correspondent banking or tiering. A settlement bank is a bank, which provides settlement services to other banks. That is, it acts as intermediary between members and non-members of a payment system.

We build a model where a payment system, a RTGS-system, competes against a settlement bank on offering settlement services to two large and two small banks. All banks can settle indirectly via the settlement bank. Both the payment system and the settlement bank maximize profits. There is sequential price setting such that the RTGS-system sets its price before the settlement bank does.

The model in this paper provides a new approach towards the analysis of indirect settlements. Competition between settlement institutions is assumed away in Lai et al. (2006) and Adams et al. (2008). In these papers, a fraction of the payments is settled indirectly by assumption. Moreover, only small banks choose between direct and indirect settlement and the payment system is not modelled explicitly in Chapman et al. (2008). As described above, all banks can settle indirectly and the payment system is modelled as a RTGS-system in the current paper.

The banks are required to choose either direct settlement via the payment system or indirect settlement via the settlement bank. Bilateral netting between banks is assumed away here. The banks' choice of settlement institution depends on the costs of settlement within the RTGS-system and the settlement bank. The costs from settlement in the RTGS-system include a membership fee and a fee per transaction. There are set-up costs related to the use of the RTGS-system, but no fixed costs to access the settlement bank. Thus, the cost of settlements within the settlement bank is a fee per transaction. The cost structure implies that large banks with a huge number of transactions tend to prefer a fixed fee and a low fee per transaction, i.e. large banks tend to prefer the RTGS-system. By the same logic, small banks tend to prefer the settlement bank.

The results show that three market equilibria can arise; 1) all banks settle indirectly via the settlement bank, 2) all banks settle directly within the RTGS-system or 3) large banks, which have many transactions, settle directly and small banks with few transactions settle indirectly. However, there are only two possible market equilibria, 1) and 2), when the settlement bank obtains a higher profit in 1) than in 3).

The market solution is inefficient in the sense that it differs from the social planner's solution. This is driven by different cost structures within the settlement systems, which works as a kind of product differentiation. Thus, the RTGS-system and the settlement bank can price above or equal to marginal costs depending on how many banks they serve with settlement services. The inefficiency is reduced with a cost-covering RTGS-system. A fully efficient market solution is reached with a welfare-maximizing RTGS-system.

The model is extended by risk of illiquidity for the banks and the settlement bank. This implies that they can be unable to settle payments. Compared with the market solution of the basic model, two additional situations can arise. First, for a high risk of illiquidity, 2) and 3) are the only equilibria. That is, the settlement bank does not serve large banks. In the second situation, there is only one equilibrium, namely 4) large banks settle indirectly and the small banks settle within the payment system. The market solution differs from the social planner's solution and this is in line with the findings in the basic model.

The third paper is entitled *Financial Soundness in Danish Banks: Does the Composition of Customers Matter?* (singleauthored). This paper considers the relationship between the banks' financial soundness and the composition of their customers. In the aftermath of the financial crisis, the exposure of banks towards certain groups of customers has come into focus. Specifically, the lending to real estate activities and farmers has been mentioned in the Danish case. The customer composition are either divided into different industries (*Real estate activities and renting*, *Farming*, *Building and construction*, *Wholesale except motor vehicles* etc.) or sectors (*Households*, *Firms*, *Government* and *Monetary and financial institutions, MFIs*).

To my knowledge, this is the first paper that analyzes the relationship between the banks' financial soundness and their lending to specific industries and sectors. Other recent papers within this field focus on the relationship between the financial soundness of banks and a) competition in the banking sector or b) the importance of bank size and foreign ownership of banks, see Uhde and Heimeshoff (2009) and Fungáčová and Solanko (2008) among others.

The data sets are unique. We have access to micro-level data for each bank's lending subdivided into sectors and industries during the period 2000-2008. The financial soundness of banks is measured by the Z-score technique. We control for bank-specific variables and macroeconomic indicators when we estimate the relation between the customer composition and the financial soundness of banks.

The first set of results is based on the data set on industries since this has the most detailed customer composition. We find that the lending to *Building and construction* and *Sale of motor vehicles and automotive fuel* affect the financial soundness of banks positively. However, the impact of the customer composition for the industry dimension is surprisingly small. What really matters is business cycle effects and the bank size. Thus, banks are less financially stable during recessions or if they are large.

The results are relatively stable towards changes in the bank-specific variables or the macroeconomic indicators, but sensitive with respect to the customer composition.

These findings are largely confirmed by the estimations on the sectoral sample. Somewhat surprising, we find that the lending to *Households* affect the financial soundness of banks significantly along with the macroeconomic indicators and the size of the banks. We expect that the industries that matter for the financial soundness of banks correspond to the sectors, which have significant influence.

The Z-score combines three different indicators for bank health in one number. We consider the Z-score components for two reasons. First, we gain a deeper understanding of which of the components that drive the overall results for the Z-score. Second, we check the robustness of the measure of financial soundness, which tends to be high for banks with a stable return over time and low for larger banks. Thus, we regress the Z-score components, profitability of banks, capital ratios and the volatility of returns, on the preferred set of explanatory variables. As a further robustness check of the capital ratio, we also regress the solvency ratio on the preferred set of regressors.

More industries (*Farming*, *Investment funds*, *Other financial service activities*, *Real estate activities and renting*, *Wholesale except motor vehicles* and *Other industries*) and sectors (*MFIs*, *Firms*, *Government*) come out significantly when we consider the components of the Z-score and the solvency ratio. Furthermore, in the data set on industries, the results for the preferred model for the Z-score seem to the driven mostly by two of the Z-score components, the capital ratio and the profitability of banks. The capital ratio drives the results for the Z-score in the sectoral sample.

To sum up, although the empirical evidence could be stronger, the results support the Basel Committee's view on the need to keep track of the banks' exposure towards certain groups of customers, including industries or economic sectors.

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Chapter 1

The Topology of Danish Interbank Money Flows

Co-authored with Morten L. Bech, Federal Reserve Bank of New York.

We thank Danmarks Nationalbank for providing us with the data set for the analysis. This paper has benefited from helpful comments from Enghin Atalay, Asger Lau Andersen, Bjarne Astrup Jensen and seminar participants in the Annual Workshop, Danish Graduate Programme in Economics, 2007; the Annual Workshop, The Danish Doctoral Educational Network in Finance, 2008; The Danish Economic Society's Annual Meeting, 2008; Danmarks Nationalbank, 2008 and Norges Bank, 2008. The views expressed do not necessarily reflect the views of Danmarks Nationalbank, the Federal Reserve Bank of New York or the Federal Reserve System. This paper is published in Banks and Bank Systems, Issue 4, 2009, p. 48-65.

Abstract

This paper presents the first topological analysis of Danish money market flows. We analyze the structure of two networks with different types of transactions. The first network is the money market network, which is driven by banks' behaviour on the interbank market, the second is the network of customer driven transactions, which is driven by banks' customers' transactions demand. We show that the structure of these networks differs. This paper adds to the new and growing literature on network topological analysis of payment systems.

Version: December 2008

Keywords: Network, Topology, Payment System, Money Market.

JEL classification: E42, G21

Introduction

The recent financial turmoil has highlighted the central role played by the interbank money markets for the smooth functioning of the financial system and implementation of monetary policy. Liquidity evaporated from many parts of the interbank money market and central banks have intervened in force and has de facto replaced private intermediation with public intermediation.

Thus, understanding the inner workings of the money market is of paramount importance in terms of analyzing and responding to financial turmoil.

Theoretical contributions have discussed whether a complete financial structure, where all banks have cross-holdings on each other, or an incomplete structure, where banks only keep the cross-holdings needed, is optimal for hindering contagion from arising, cf. Allen and Gale (2000), Freixas and Parigi (1998) and Freixas et al. (2000). Basically, this is a choice between liquidity saving (banks can keep smaller liquidity reserves if they can raise liquidity via the interbank market) and contagion risk (banks become fragile towards disturbances - in other banks or the network as a whole - if they use the interbank market). In theoretical models, central banks are assumed to make optimal interventions in the interbank market whereby they can hinder contagion from arising, cf. Freixas (2000). But the risk of contagion effects and central banks' possible actions depend crucially on the actual structures on the interbank market.

The large-value payments system is in general the settlement platform for the interbank money market. The lion share of the money market transactions are settled on this platform. Therefore, disruptions in the large-value payment systems can in and by themselves create dislocations in the money market. Moreover, disruptions for a single bank can affect all other banks in the network. Thus, resiliency is crucial. Besides the size of interbank exposures on the money market, the risk of contagion effects also depends on the size of banks and these banks' locations in a network, cf. Lublóy (2006) and Upper and Worms (2004).

Network topology provides a framework for analyzing the inner working of interbank money flows. During the last couple of years, the physical theory of networks has developed rapidly as it has been shown that many physical networks have several characteristics in common. That is, payment systems have many things in common with other physical networks like the internet or networks for electricity or water supply. In recent years, a new and growing literature on the functioning of payments systems has emerged using the network topological approach. This has led to important new insights into the functioning of financial networks in the US, Japan, Austria and Hungary among others, cf. Soramäki et al. (2007), Inaoka et al. (2004), Boss et. al. (2004), and Lublóy (2006).

Data from the transaction journal of the Danish large-value payment system are used to analyze two economically different networks of interbank money flows. The first network consists of money market transactions, the second of all other transactions. That is, the primary transactions in the payments network are banks' proprietary transactions and customer driven transactions. In contrast to this, the money market network consists of overnight money market loans.

We find that the structure of these networks differ considerably. In the payments network, two commercial banks are responsible for a rather large share of the total activity, whereas there are several major banks in the money market. Both networks are rather concentrated as 10 banks are responsible for most of the transactions in both networks. Seasonal effects are important for the size of the networks. The payments network extends by the turn of the month and quarter and on the first business day following a holiday. In contrast to this, weekday effects drive the calendar effects observed in the money market. Event studies of an operational disruption do not indicate any troubles with regard to the workings of the large-value payment system, whereas payments disruptions by a major participant change the structure of the networks and the level of their activities.

This paper is organized as follows. In section 3.1 we describe the data and the algorithm used for dividing the data into money market transactions and other transactions. We analyze the network topologies of these economically different networks, which are labelled money market network respectively payments network. Illustrations of these networks are presented in section 3.2 and section 3.3 is devoted to a components analysis of the active banks in each network on daily basis. In section 3.4, the summary statistics of topological measures are presented and we analyze the permanency of links and nodes, which are of importance for the stability of the networks. Moreover, correlations between basic topological measures and seasonal effects are discussed. Section 3.5 is devoted to event studies of two recent incidents in the Danish large-value payment system. Finally, section 3.6 concludes.

3.1 The data set

We have access to all transactions originated over the Danish large-value payment system (Kronos) in 2006[1]. The system was open daily from 7.00 a.m. to 3.30 p.m. and 130 banks, including the central bank and branches of foreign banks, were members of the system in 2006.

Banks use large-value payment systems to settle obligations on behalf of their customers as well as their own obligations arising from proprietary operations. An important component of the latter is overnight money market activities. We use an algorithm similarly to Furfine (1999) to separate out from the transaction data set the deliveries and returns of overnight money market loans. We refer to all other transactions as payments.

The algorithm defines a transaction as an overnight money market loan if there is a transaction from bank A to bank B on day t and a reverse transaction from B to A on the same amount plus interest on the following day. The details of the algorithm are explained in the appendix.

A couple of caveats are appropriated as the algorithm's selection criteria do not select overnight money market transactions perfectly. First, the algorithm can only capture overnight loans transferred via the payment system. Second, we can only observe the settlement time of the transactions but not the actual point in time where a bank enter into an agreement on an uncollateralized overnight loan with another bank. An uncollateralized money market loan can be agreed upon earlier in the day of settlement or on previous days[2]. Third, the algorithm does not identify term loans. However, this market is small in Denmark as more than 90

[1] We exclude transfers to and from auxiliary systems such as the Continuous Linked Settlement for FX trades, CLS, the Danish automated clearing house (Sumclearing) and the Danish central securities depository (VP). The purpose, value and timing of these settlements differ fundamentally from bank to bank transfers.

[2] Tomorrow-next and spot-next trades, which also imply pairs of transactions between two banks on two consecutive days, are agreed upon 1 respectively 2 days before the settlements of the trades.

% of the banks lending in the money market for deposits have maturity less than 7 days[3]. Fourth, the borrower and lender registered by the payment system may not be the final ones due to correspondent banking. Despite these drawbacks the algorithm has been used on similar Danish data by Amundsen and Arnt (2005). Thus we will adopt this algorithm and analyze the network topology for the money market on the available data.

We identify two economically different networks by the algorithm's division of our data

1. money market network, which consists of overnight money market loans identified by the algorithm

2. payments network consisting of all other transactions, primarily the settlement of customer driven transactions and banks' proprietary transactions[4].

The basic characteristics for the money market network and the payments network are shown in table 3.1 along with results for the full data set.

For each of the business days in 2006 we construct a money market network and a payments network and we use these to obtain aggregated annual results. Each network consists of a number of nodes and links. The banks are nodes and the transactions form links between banks. Two banks are said to be linked if there is at least one transaction between them. Links can be directed, where the direction follows the flow of money, i.e. from lender to borrower and from payer to payee, or undirected. If there are more transactions via the same link, the transactions in a network are weighted. The weights are the sum of either value or the number of transactions between two banks.

[3] This is calculated from data on turnover and interest rates in the Danish market for uncollateralized overnight money market lending. In 2006, 12 banks reported these data to the Danish central bank. The central bank estimates an average tomorrow-next interest rate, which is published daily to the market. See Damm and Pedersen (1997) for a detailed description.

[4] All transactions to/from the central bank are in this network since the central bank does not engage in unsecured overnight lending.

Table 3.1: Characteristics of the networks, totals for 2006

	Transactions	Payments	Money market
Active banks	130	130	70
Volume of transactions (thousands)	602.7	574.6	28.2
Value of transactions (trillion DKK)	33.3	26.8	6.5
Mean value of transactions (million DKK)	55.3	46.7	230.7
Volume of transactions (per cent)	100.0	95.3	4.7
Value of transactions (per cent)	100.0	80.5	19.5
10 largest banks' share of			
-Volume of transactions	87.3	88.9	53.7
-Value of transactions	91.1	93.1	83.0

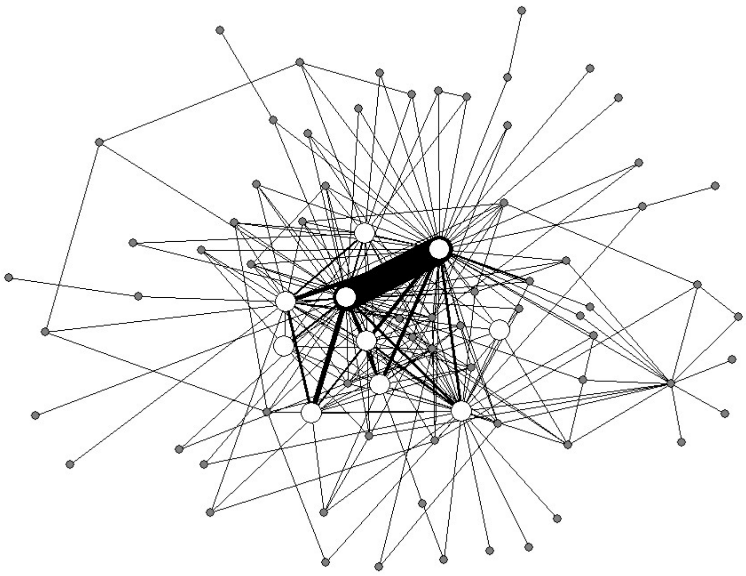
Note: Transactions denotes the results for the full data set. Outgoing volume and value from the banks are used to estimate the shares reported.

3.2 Illustration of the networks

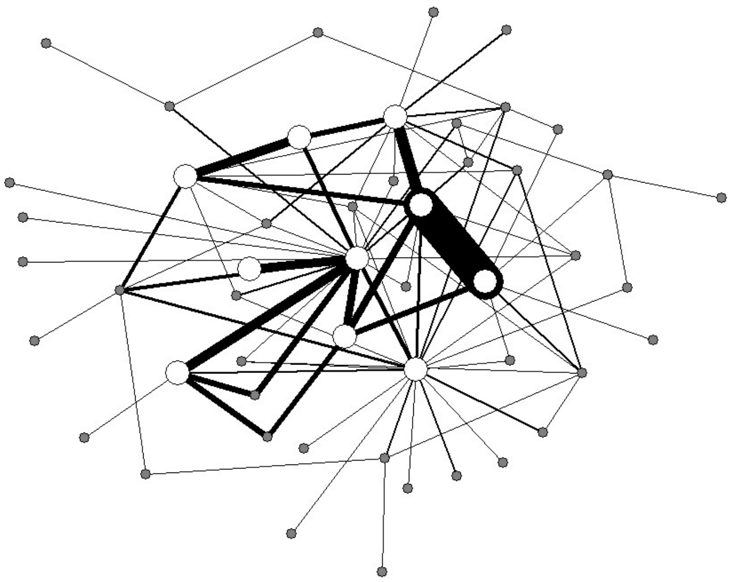
The payments and money market networks for a single day in 2006 are illustrated in figure 3.1. The thickness of the links is scaled by the value transferred across and the ten banks, which transferred the most money in either network, are highlighted by larger white nodes. Three structural features are immediately obvious. First, more banks are active in the payments network than in the money market network. Second, two large commercial banks play a major role in both networks, but somewhat surprising the important bank-pair in the payments network *is different from* the major bank-pair in the money market. Third, the top-10 banks account for a significant share of the turnover in terms of values in both networks (93.1 and 83.0 per cent respectively), which is quite natural as large banks tend to be more connected than other banks. However the top-10 banks' market share in terms of volume is 53.7 per cent in terms of the number of loans in the money market network, cf. table 3.1. This reflects that the average loan size of the top-10 banks is substantially larger than for other banks in the money market (the average loan size for top-10 banks is 356.6 million DKK and 84.5 million DKK for other banks).

In order to better understand the structure of flows among large banks we plot the network of only the ten largest banks in figure 3.2. We do so in two ways.

Figure 3.1: Payments and money market networks



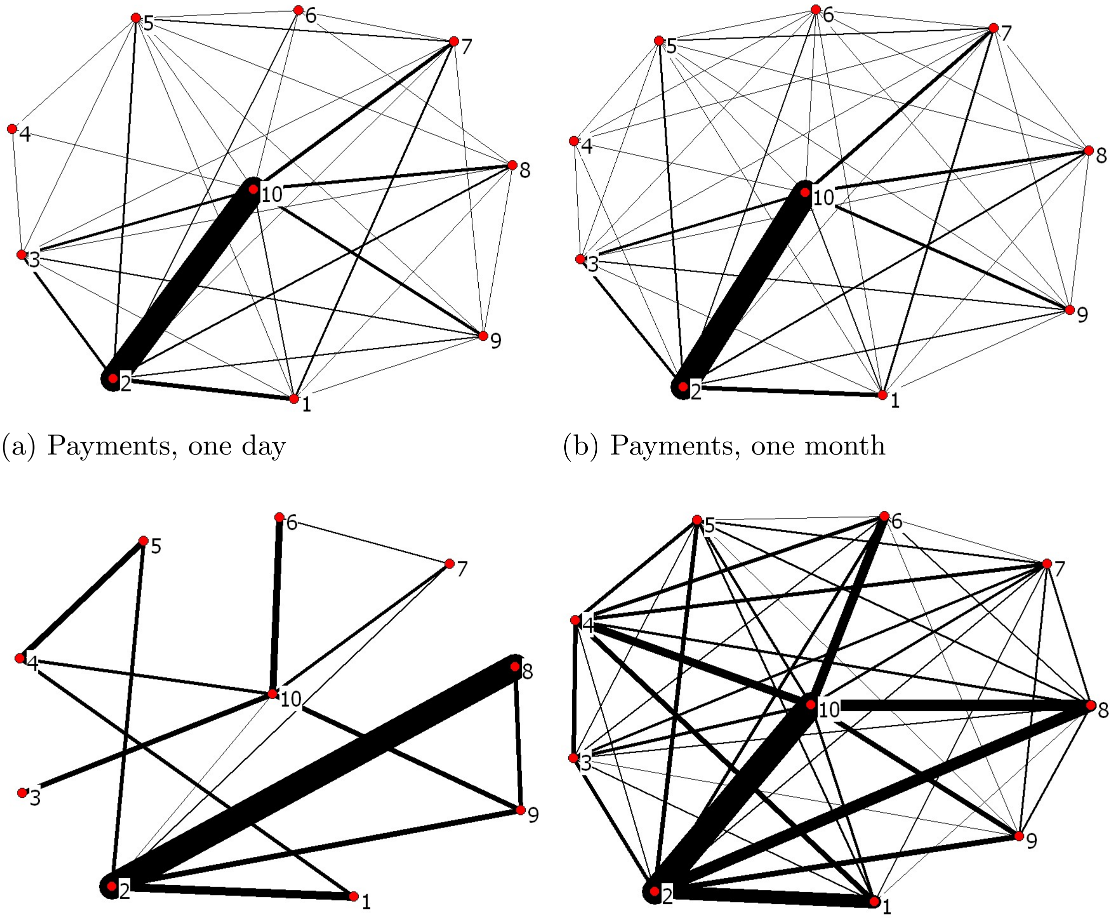
(a) Payments



(b) Money market

Note: The top-10 banks (large and white coloured) are identified from total value of outgoing payments in 2006. Links are undirected and weighted by value.

Figure 3.2: Graphical illustration of the centre of the networks (measured in value)



(a) Payments, one day

(b) Payments, one month

(c) Money market, one day

(d) Money market, one month

Note: Data for total payments between the ten largest banks in March 2006 used in the one-month-figures. Since the weighting of links in each network depends on the total value of transactions in each network, the thickness of the links is not comparable between networks. The centre of each network consists of the 10 largest banks measured by the total outgoing value of transactions. The top-10 banks are all commercial banks and bank 2-10 are the same in both networks, whereas bank 1 differ between the payments network and the money market network.

In the first column of figure 3.2 we show networks based on transactions for one day whereas the second column show the networks based on transactions for an entire month. The structural differences between the payments and the money market networks are striking. The one day centre of the payments network is almost complete[5] whereas the degree of completeness is 20.0 per cent on average in the centre of the one day money market.

3.3 Components

Nodes in a network can be divided into groups depending on how they connect to other nodes. A network is comprised by a set of disconnected components within which nodes are linked by an undirected path and do not have links to nodes outside the component. Many empirical investigations find that one of the disconnected components is several orders of magnitude larger than the other disconnected components, cf. Dorogovtsev and Mendes (2002), Albert and Barabási (2002), Soramäki et al. (2007). In contrast, we find that the payment and interbank money market networks consist only of a single component on every day.

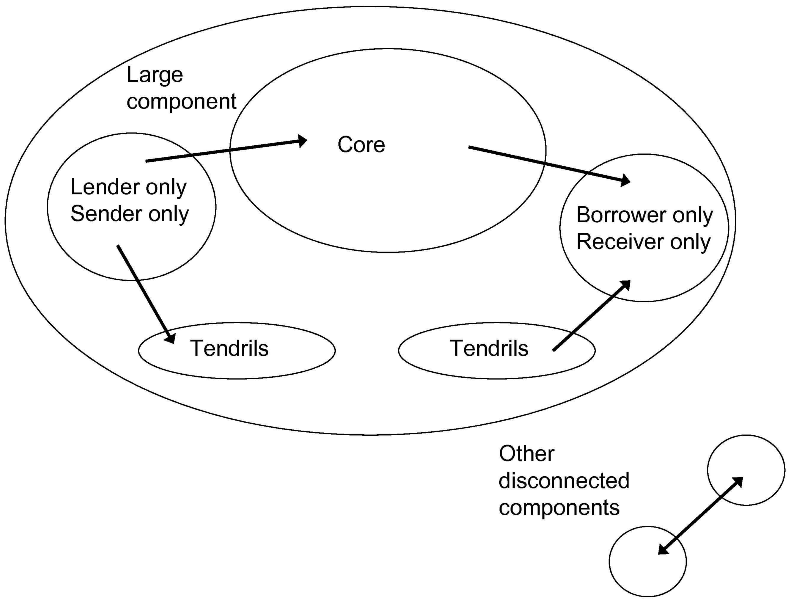
We divide the networks into four subcomponents[6], cf. table 3.2. First, we have the core which consists of banks that are connected to each other via a directed path. Attached to the core are two peripheral set of banks that are on a directed path to or from the core. As such the core facilitates the circulation (or intermediation) of funds within the network whereas banks in the peripheral groups are either senders or receivers of funds only. Finally, a limited number of banks belong to so-called tendrils, which consists of nodes that are on a directed path to or from the peripheral components.

Our results show that 89.0±5.3 (the mean plus/minus the standard deviation

[5]The degree of completeness is at its maximum of 100 per cent in a complete network and at its minimum in a tree network, where the degree of completeness is equal to 1 divided by the number of nodes. Complete and tree networks are stylized networks, which are not observed empirically. See the appendix for an illustration of stylized networks.

[6]In the network topology methodology the large component is known as the *Giant Weakly Connected Component.* The core of the network is denoted the *Giant Strongly Connected Component* and the lender/sender (borrower/receiver) only components as the *Giant In-Component* (*Giant Out-Component).* Finally, the other disconnected components are denoted *Disconnected Components*, cf. Dorogovtsev and Mendes (2002).

Figure 3.3: A network and its components



across days) banks are active in the payments network on average in 2006. 60.3±6.2 banks belong to the core, cf. table 3.2. The money market network is smaller with only 43.6±4.1 banks being active on an average day in 2006. The size of the core in the money market was 27.4±6.8.

In both networks, most of the transactions are transferred within the core, cf. table 3.3. As measured by capital[7], banks in the core are larger than banks in other components in both networks. As a number of smaller banks are active in the payments network only the average capital level of banks is larger in the money market than in the payments network.

The lion share of value in both networks is transferred within their respective cores. For the payments network the share is 99.6 per cent of the total value, whereas in the money market network it is 93.5 per cent. Banks in the peripheral groups comprise almost all of the remaining value in both networks.

[7] Banks' capital is their productively employed capital, which comprises deposits, issued bonds, subordinated capital contributions and equity capital. Banks' productively employed capital is used to determine the fixed membership fee of the Danish large-value payment system.

Table 3.2: Components in the networks

	Payments	Money Market
Nodes connected by a directed path	The core	The core
Nodes on a directed path to core/tendril	The sender only	The lender only
Nodes on a directed path from core/tendril	The receiver only	The borrower only
Other nodes	Tendril	Tendril

Note: The lender/sender (borrower/receiver) only component can submit (receive) transactions to (from) either the core of the network or to (from) a tendril.

3.4 Summary statistics for the network topologies

A detailed analysis of the structural differences between the networks across time is difficult by visualization. Therefore, we consider a set of statistical measures common in the network topological approach in this section[8]. We will focus on statistics of network activity in the core of the networks as the core plays a key role in determining the activity and the well-functioning of a payment systems network due to its intermediary role in distributing liquidity among banks in demand and supply of it, cf. table 3.3. Furthermore, this is in line with the approach in Soramäki et al. (2007), Bech and Atalay (2008) and Pröpper et al. (2008).

3.4.1 Characteristics of the networks

The turnover in the payments network[9] is larger both in value and volume than in the money market network and number of active banks are largest in the payments network, cf. table 3.4. The average value transferred via a link in the money market network is slightly lower than in the payments network (the link weight in value is (322.7 million DKK respectively 374.7 million DKK on average), whereas the volume transferred via a link in the payments network is significantly larger than

[8]The topological measures used are explained in the appendix. Hekmat (2006) gives a thorough description of the physical concepts in network topology.

[9]The summary statistics for the payments network are in line with the results for the transactions network (the whole data set) since most of the observations in the transactions network are the same as in the payments network, see table A2 in the appendix.

Table 3.3: Components of the networks, 2006

Component	Comp.'s shares Per cent	Mean	Median	Min	Max	Std	Value Out	Value In	Capital, Average Billion DKK
		Number of nodes					Per cent		
Payments									
Network	100.0	89.0	89.0	76.0	113.0	5.3	100.0	100.0	23.1
Core	67.7	60.3	60.0	48.0	86.0	6.2	99.6	99.6	33.2
Sender only	16.2	14.4	14.5	3.0	24.0	3.8	0.3	0.0	2.6
Receiver only	15.1	13.5	13.0	4.0	29.0	4.0	0.0	0.3	2.7
Tendrils	0.9	0.9	0.0	0.0	5.0	1.1	0.0	0.0	2.0
Money market									
Network	100.0	43.6	44.0	32.0	53.0	4.1	100.0	100.0	42.3
Core	62.9	27.4	28.0	3.0	43.0	6.8	93.5	93.3	61.6
Lender only	16.9	7.4	6.0	0.0	24.0	5.1	5.5	0.7	11.0
Borrower only	16.9	7.4	6.0	0.0	27.0	4.9	0.7	5.7	10.9
Tendrils	3.3	1.4	1.0	0.0	24.0	2.3	0.3	0.2	8.3

Note: The components' shares (Comp.'s shares) of the network are calculated from the mean of the number of nodes. The shares of the value are calculated for in- respectively outgoing payments and the last column contains the average level of capital for the banks in each component. The large maximum value of tendrils in the money market occurs on the first business day in 2006.

in the money market network. This explains the difference in the average size of a transaction in the two networks in table 3.1.

40 banks were active on each business day in the payments network and they handled 99.2 per cent of the total value (30.8 per cent of the total volume). Moreover, 26 links were permanent as they existed on each business day and these accounted for 74.6 per cent of the value transferred (77.6 per cent of the volume). Thus, most links only exist for few business days. This is in contrast the Hungarian large-value payment system, where a larger fraction if the value is transferred via permanent links, cf. Lublóy (2006). One reason might be that the Hungarian system has larger banks as its members, whereas banks are of different size in the Danish RTGS-system. In the money market, 7 banks were active on all business days and they handled 10 per cent of the volume and 66.7 per cent of the value. The most permanent link existed for 189 days out of 252 business days and this link handled 19.2 per cent of the total turnover in the money market. Thus, in both networks a number of banks handle a large share of the total value of transactions and most links exist for a few days only as illustrated in figure 3.5.

Although the top-10 banks in both networks tend to form links with almost all other top-10 banks in figure 3.2, the actual number of links formed is substantially smaller than the potential number of links when we consider the networks in general.

For both networks only 1 out of 10 possible links are formed on a given day with a slightly lower connectivity in the payments network (8.3±0.8 per cent) than in the money market network (11.2±5.8 per cent). Thus, banks in the periphery of a network tend to form fewer links than the banks in the core. The reciprocity, which measures the share of links between banks for which there is a link in the opposite direction, is virtually the same in the two networks as 1 of out 4 links have transactions in both directions. The reciprocity in the money market network is substantially larger than in the Fed Funds Market, whereas the reciprocity in the payments network is a bit larger than in Fedwire. In the payments network, there is a 50 per cent chance that two neighbours of a node are also linked to each other whereas there is only a 1 out of 5 chance in the money market network. In both networks, the clustering coefficient is much higher than the connectivity so neither of the networks is random[10].

An important characteristic of a node in a network is the number of links, which originate from a node and the number of links terminating in a node. The average number of links per node in the payments network is 4.8±0.4, which is almost double the average node degree of 2.7±0.3 in the money market network. In the payments network, the maximum number of links originating from (terminating in) an active bank is 29.0±3.9 (34.6±4.4), cf. table A.1 in the appendix. In the money market network, the number of links originating from (terminating in) an active bank is 10.3±3.4 (10.3±3.6). That is, banks within the money market tend to have fewer links to other banks than active banks in the payments network.

The distribution of links originating from (terminating in) nodes (out-degrees respectively in-degrees) are fat-tailed, cf. figure 3.8a. A number of studies have shown that in- and out-degrees in large-value payment systems in the US, Japan and Austria follow power-laws[11], cf. Inaoka et al. (2004), Soramäki et al. (2007)

[10] The clustering coefficient is equal to the connectivity in a random network. A random network is constructed by adding links at random to a given set of nodes. This is a stylized type of network, which is unobserved in reality.

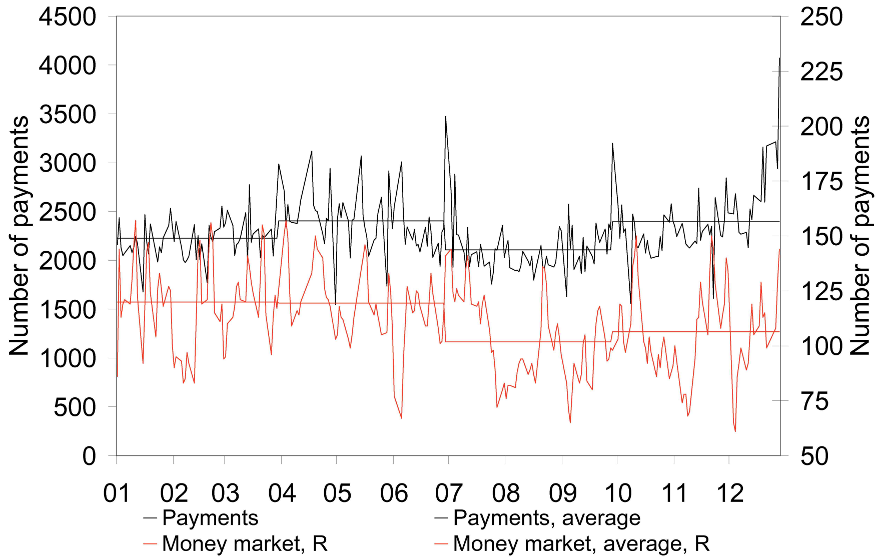
[11] A power-law is a distribution for which there is a scale effect, i.e. $P(X = x) \sim x^{-\gamma}$.

Table 3.4: Summary statistics, payments and money market networks, 2006

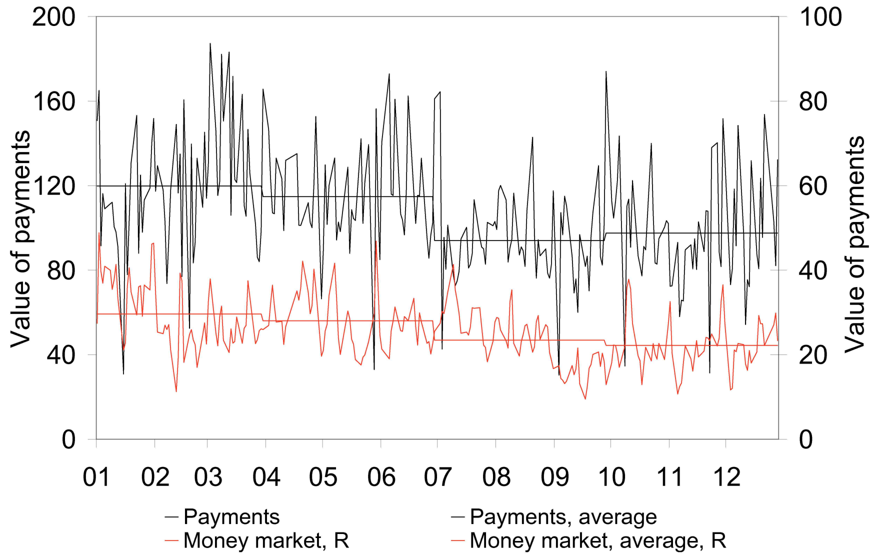
Payments	Mean	Median	Min	Max	Std	Mean Fedwire
Volume	2,162.4	2,127.0	1,493.0	3,434.0	283.8	436.0
Value	105.5	101.3	29.5	186.9	27.3	1.3
Nodes	60.3	60.0	48.0	86.0	6.2	5,086.0
Links	282.6	277.0	202.0	489.0	40.9	76,614.0
Connectivity, per cent	8.3	8.1	6.7	11.2	0.8	0.3
Reciprocity, per cent	22.8	22.8	18.0	27.3	1.8	21.5
Clustering	0.5	0.5	0.4	0.7	0.1	0.5
Average path length	2.5	2.5	2.3	2.7	0.1	2.6
Average node degree, k	4.8	4.7	4.0	6.4	0.3	15.2
Link weight, value	0.4	0.4	0.1	0.7	0.1	15.2
Link weight, volume	7.7	7.7	5.0	10.1	0.8	5.2
Node strength, value	1.8	1.7	0.5	3.4	0.5	n.a.
Node strength, volume	36.7	36.3	24.1	54.6	4.3	n.a.
Money market						Fed Funds Market
Volume	86.4	88.0	4.0	144.0	25.9	2.6
Value	22.9	22.1	0.3	45.2	8.1	0.3
Nodes	27.4	28.0	3.0	43.0	6.8	470.2
Links	75.0	76.0	4.0	132.0	23.3	1,543.0
Connectivity, per cent	11.2	10.2	6.7	66.7	5.8	0.7
Reciprocity, per cent	26.2	26.4	10.0	50.0	5.5	6.5
Clustering	0.2	0.2	0.0	0.5	0.1	0.1
Average path length	2.9	2.9	1.3	4.6	0.4	2.7
Average node degree, k	2.7	2.7	1.3	3.5	0.3	3.3
Link weight, value	0.3	0.3	0.1	1.5	0.1	219.0
Link weight, volume	1.2	1.1	1.0	1.8	0.1	1.7
Node strength, value	0.9	0.8	0.1	2.0	0.3	719.0
Node strength, volume	3.1	3.1	1.3	4.3	0.4	5.5

Note: The value, link weight in value and node strength in value are in billion DKK. Clustering and the average path length are estimated using payments submitted from a node. The summary statistics refer to the average of the daily observations for the core. Overnight loans between banks are borrowed or lend in the Market for Federal Funds (Fed Funds Market) in the US. The Fedwire Funds Service (Fedwire) is a real-time gross settlement system operated by the Federal Reserve System in the US. Data for the Fedwire and the Fed Funds Market are from Soramäki et al. (2007) and Bech and Atalay (2008). The volume of transactions in Fedwire and the Fed Funds Market are in thousands and the value in trillion USD, the link weight and node strengh in value are in million USD. Node strength is not available for the Fedwire in Soramäki et al. (2007).

Figure 3.4: Activity of the payments and money market networks, Volume and value, 2006



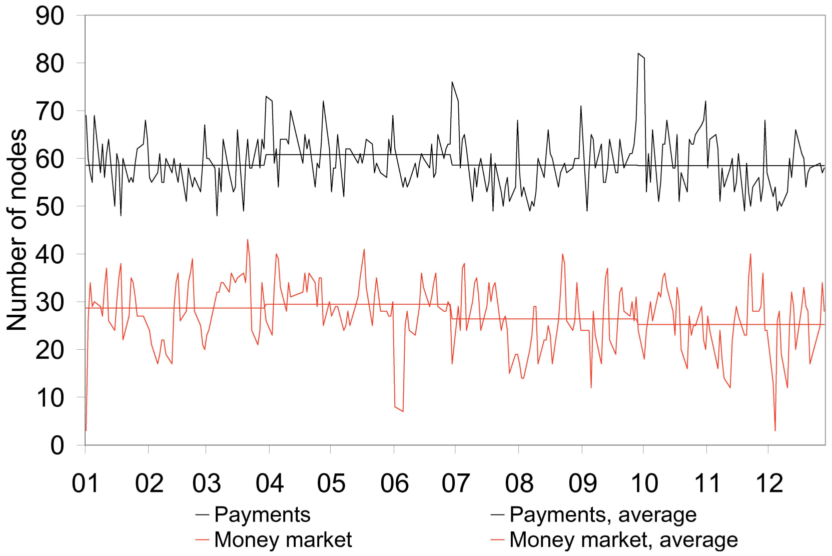
(a) Volume



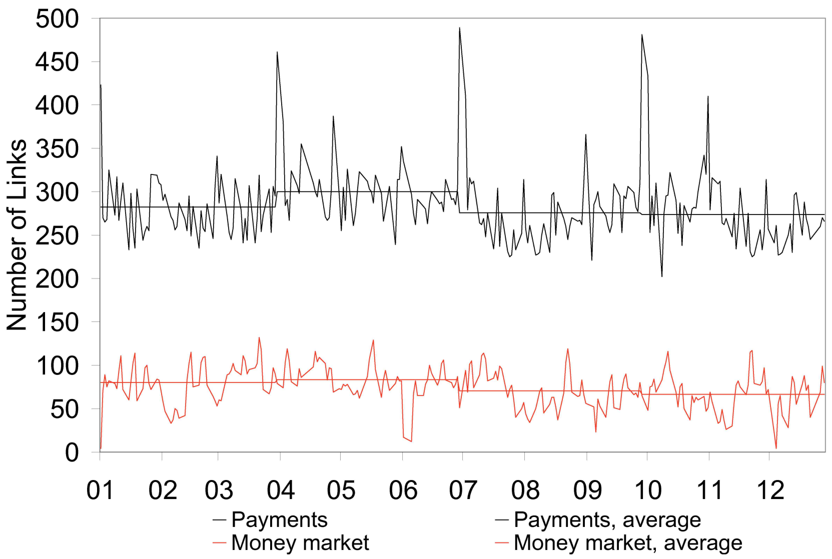
(b) Value

Note: All figures are for the core in 2006 and the months are labeled with numbers from 1 to 12. All figures include quarterly averages of the variables. The value of payments (panel b) is in billion DKK. Even though the value is downward sloping and the volume increases during the year in the payments network, the average value of a payment has been almost unchanged in the period 2003-2007.

Figure 3.5: Activity of the payments and money market networks,
Nodes and links, 2006



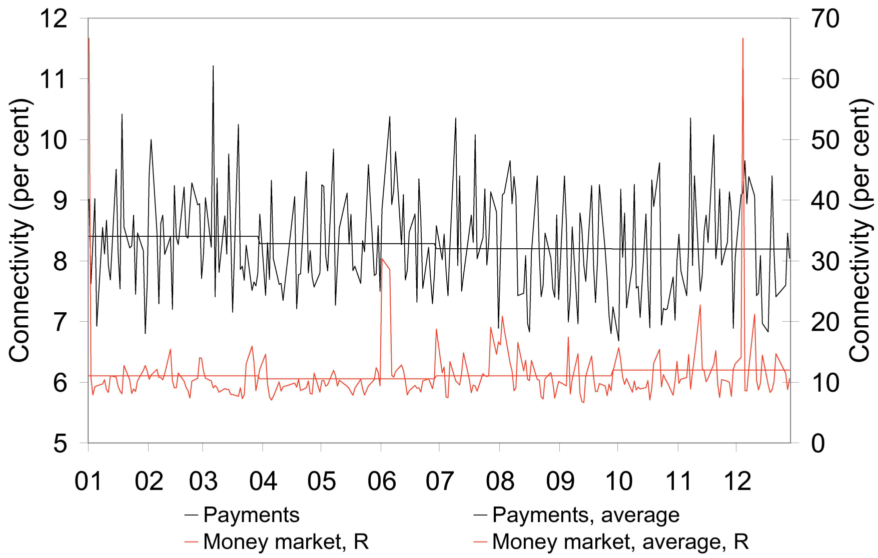
(a) Nodes



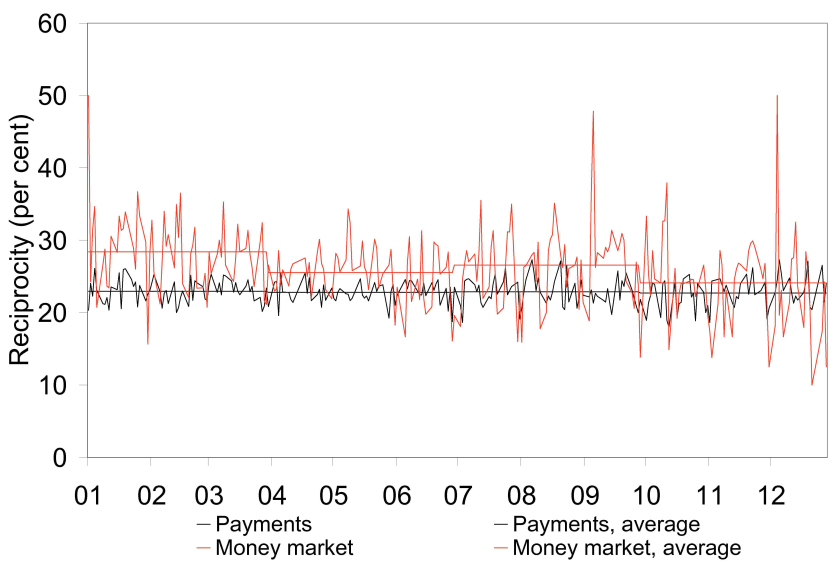
(b) Links

Note: All figures are for the core in 2006 and the months are labeled with numbers from 1 to 12. All figures include quarterly averages of the variables.

Figure 3.6: Activity of the payments and money market networks, Connectivity and reciprocity, 2006



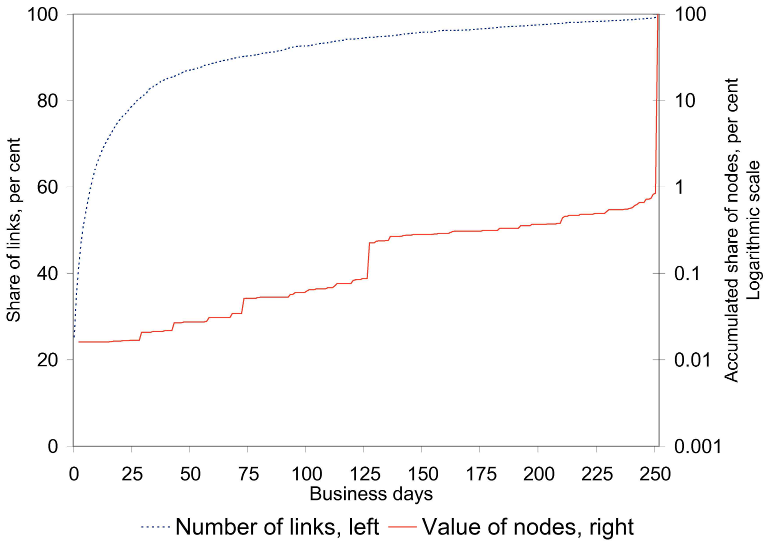
(a) Connectivity



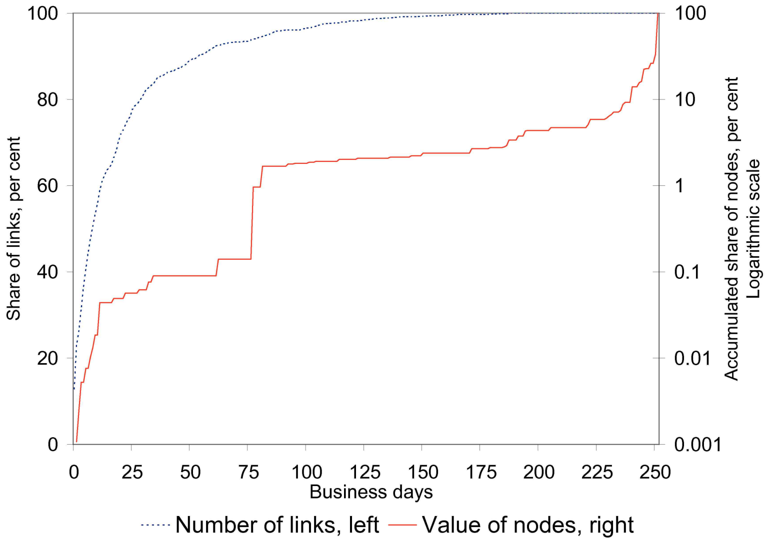
(b) Reciprocity

Note: All figures are for the core in 2006 and the months are labeled with numbers from 1 to 12. All figures include quarterly averages of the variables. The connectivity for the money market is measured on the right axis in panel a.

Figure 3.7: Frequency of links and nodes



(a) Payments



(b) Money market

Note: The value of nodes (number of links) is measured in per cent and accumulated and plotted against the number of business days. The value of nodes is measured on a logarithmic scale. The data are for the whole network of interconnected banks.

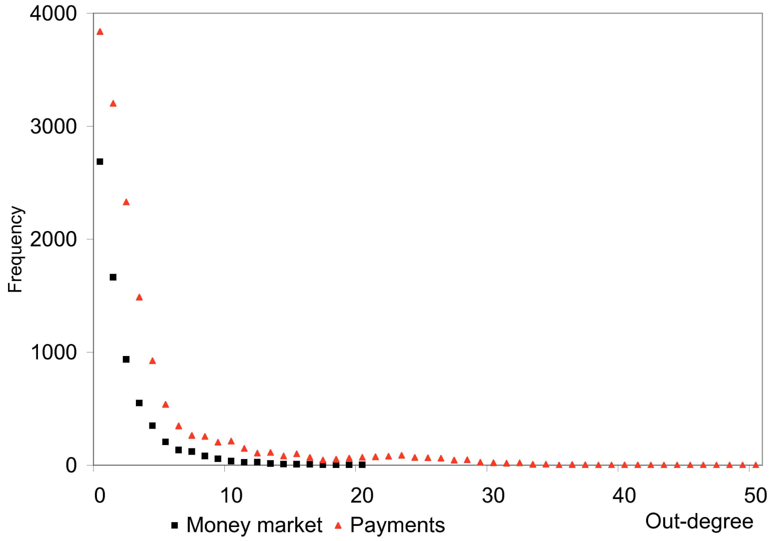
and Boss et al. (2004). In a random network, the distributions of in- and out-degrees follow a Poisson distribution, cf. Dorogovtsev and Mendes (2002) and Newman (2005). Neither a power-law distribution, nor a Poisson distribution capture the distribution of the in- and out-degrees correctly in the Danish case, cf. figure 3.8b and 3.9. In the payments network, the exponential distribution or the negative binomial distribution capture the actual distributions of in- and out-degrees quite well, whereas the exponential distribution is closest to the actual values of in- and out-degrees for the money market network, cf. figure 3.9.

An omnipresent question in network theory is the relative importance of different nodes and links usually referred to as centrality. We have already discussed the notion of degree above. The most connected bank on any given day in our sample had 53 outgoing (55 incoming) links for the payments network and 21 outgoing (24 incoming) links for the money market network. Another way to measure importance is node strength which measures the amount (or number) of payments or loans processed by a participant. According to this measure the largest node across all days processed outgoing payments worth 74.2 billion DKK in the payments network and lend out loans worth 21.1 billion DKK in the money market network on any given day. The largest (directed) link between any two banks in the two networks transferred 58.8 billion DKK worth of payments and 12.2 billion DKK worth of loans. In a relative sense the largest node and link in the payments network accounted for 52.9 and 43.7 per cent, respectively, of the total value transferred on any day. In the money market the equivalent "market share" numbers where 71.0 and 64.5 percent, respectively.

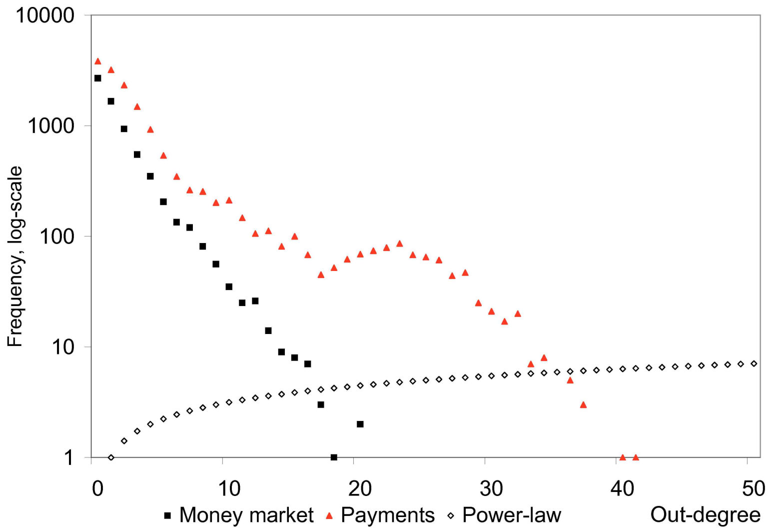
Another measure of centrality is betweenness, which is a measure of the number of paths between other nodes that run through node i. The more paths node i handles, the more central is this node in the network. The measure can also be applied for links to identify the most important links between banks. Results in table A.1 in the appendix show that the average betweenness for links is almost identical in both networks (29.2$\pm$8.4 in the money market and 30.3$\pm$3.7 for the payments network), whereas the betweenness for nodes in the money market network is 40 per cent lower than in the payments network, i.e. each node in the money market handles fewer paths than banks in the payment network.

The average path length is the average number of links, which connects two

Figure 3.8: Distributions of out-degrees



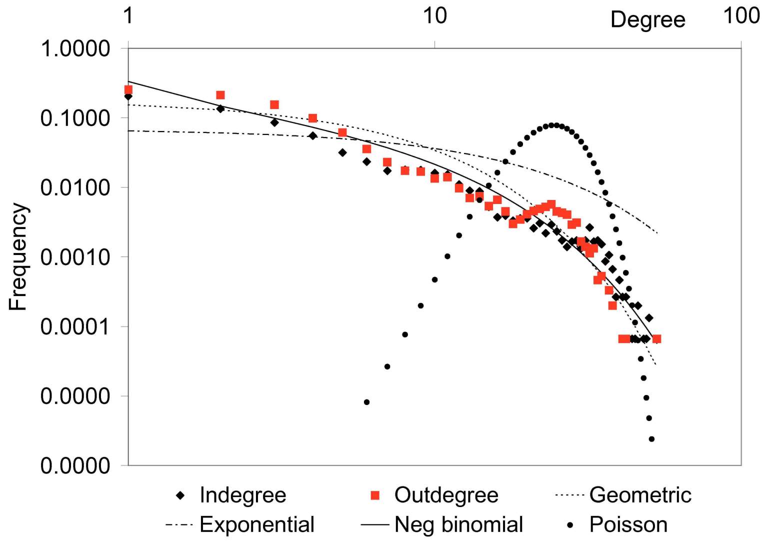
(a) Distribution of out-degrees



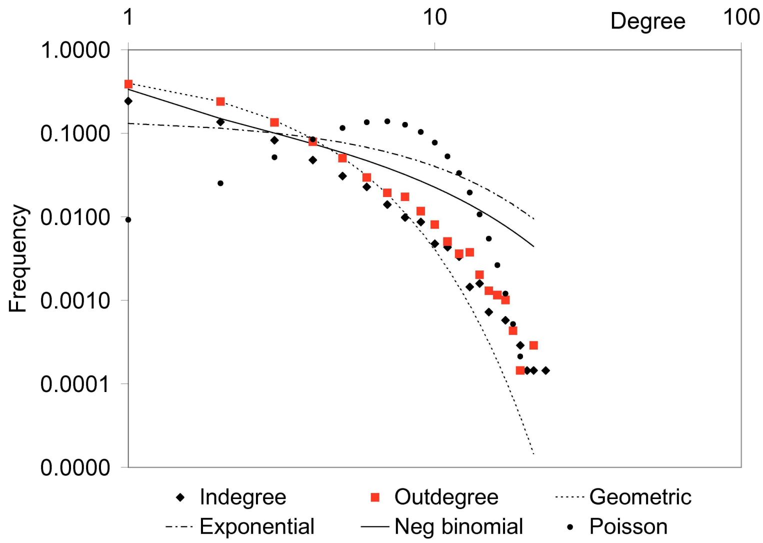
(b) Log-scale including power-law

Note: The y-axis is in log-scale in panel (b). The data are for the whole network of interconnected banks. Only out-degrees are shown here, but figures for in-degrees are similar.

Figure 3.9: Distributions of in- and out-degrees



(a) Payments



(b) Money market

Note: Both x- and y-axis are logarithmic. The data are for the whole network of interconnected banks. The leftwing tail of the Poisson distribution in panel (a) has been cut off to keep a clear picture. This choice is reasonable since the in- and out-degrees for the payments network are clearly not Poisson distributed.

banks via the shortest possible path, i.e. the average path length measures across how many links 1 DKK must pass to reach another bank. Our results show an average path length of 2.5±0.1 in the payments network and 2.9±0.4 in the money market, cf. table 3.4. The corresponding values for Fedwire and the Fed Funds Market are 2.6 respectively 2.7, cf. Soramäki et al. (2007) and Bech and Atalay (2008). The maximum distance between two banks (measured by the number of links) is the diameter, which is 5.5±0.7 for payments network and 6.7±1.3 for the money market network, cf. table A.1 in the appendix. This is substantially smaller than the diameter in Fedwire of 6.6 on average and the diameter in the Fed Funds Market of 7.3, cf. Soramäki et al. (2007) and Bech and Atalay (2008).

More than half of the other banks in the payments network can be reached within 2 nodes cf. table A.1. Increasing the distance to 3 implies that 91.2±2.7 per cent of the nodes can be reached and by the distance 5 almost all banks are reachable. In a study for the Fedwire, Soramäki et al. (2007, table 3) finds that the mass distribution function reaches almost 100 percent within the distance 4. The larger distance between banks in the money market implies that only 42.1±9.5 (71.6±10.0) per cent of the banks can be reached within a distance of 2 (3).

3.4.2 Correlations of network statistics and seasonal effects

The correlation coefficients between the basic network statistics confirm the patterns in figure 3.4-3.6, where the where the activity in volume and value tend to covariate with the size of the networks (nodes and links) in both networks, see table 3.5. In the payments network, connectivity is negatively correlated with the number of active banks and links. This result is contrary to Soramäki et al. (2007), which find that the correlation between nodes (links) and connectivity are quite strong and positive in Fedwire. Moreover, the reciprocity is uncorrelated with the activity (value and volume) so the payments network does not become denser as the activity increases. The connectivity in the money market is negatively related to any measure of activity (value and volume) and size (nodes and links). In general, the denseness of the money market network (reciprocity) is uncorrelated with any other measure with the possible exception of the slightly positive correlation between reciprocity and connectivity. This reflects that a bank, which become active in the money market, tend to have only a few links to other banks.

Table 3.5: Correlations of basic network properties, 2006

Payments

	Value	Volume	Nodes	Links	Connectivity	Reciprocity
Value	1.00	0.58	0.25	0.44	0.14	0.26
Volume		1.00	0.50	0.68	-0.02	0.09
Nodes			1.00	0.86	-0.72	-0.36
Links				1.00	-0.28	-0.17
Connectivity					1.00	0.48
Reciprocity						1.00

Money market

	Value	Volume	Nodes	Links	Connectivity	Reciprocity
Value	1.00	0.62	0.49	0.55	-0.34	0.04
Volume		1.00	0.92	0.98	-0.57	0.09
Nodes			1.00	0.95	-0.69	0.05
Links				1.00	-0.57	0.07
Connectivity					1.00	0.25
Reciprocity						1.00

There seems to be a seasonal pattern in figure 3.4-3.6, especially around quarter ends. To test for this we regress 8 different topological measures on a set of dummies for holidays, weekdays and liquidity provisions by the Danish central bank in addition to the regular liquidity adjustments on Fridays. Results are shown in table B.1 and B.2 in the appendix.

For the payments network, the effects on the first business day following Danish or US holidays are significant for links, value, volume and average node degree. This network is extended at every turn of month and quarter both considering the number of active banks, links, value, volume and average node degree. Moreover the connectivity decreases significantly by the turn of quarter. These effects are due to large quarterly interest and repayment on mortgage loans, which is the prime source of funds in the Danish housing market, and monthly payments of salaries, social benefits and taxes etc., which initiate more transactions that usual. The network is largest on Fridays (in nodes, links and value) and smaller by the beginning of the week (in nodes, links, volume and average path length). Both planned and unexpected liquidity adjustments increase the number of links and the average node degree significantly.

For the money market there are significant weekday effects for nodes, links and volume, especially on Fridays, which is the first day in the weekly liquidity schedule. This affects connectivity positively. The same pattern is observed by the turn of the month, but only the average node degree and the connectivity are positively affected at the turn of quarter. Unexpected liquidity adjustments increase the average node degree and decrease the average path length. In contrast to this, there are no effects from expected liquidity adjustments or from holidays.

3.5 Event studies

In order to investigate how the networks respond to disturbances we consider two case studies of operational events[12]. The first event is an intraday operational disruption of the Danish large-value payment system; the second is payment disruptions by a major participant on multiple days.

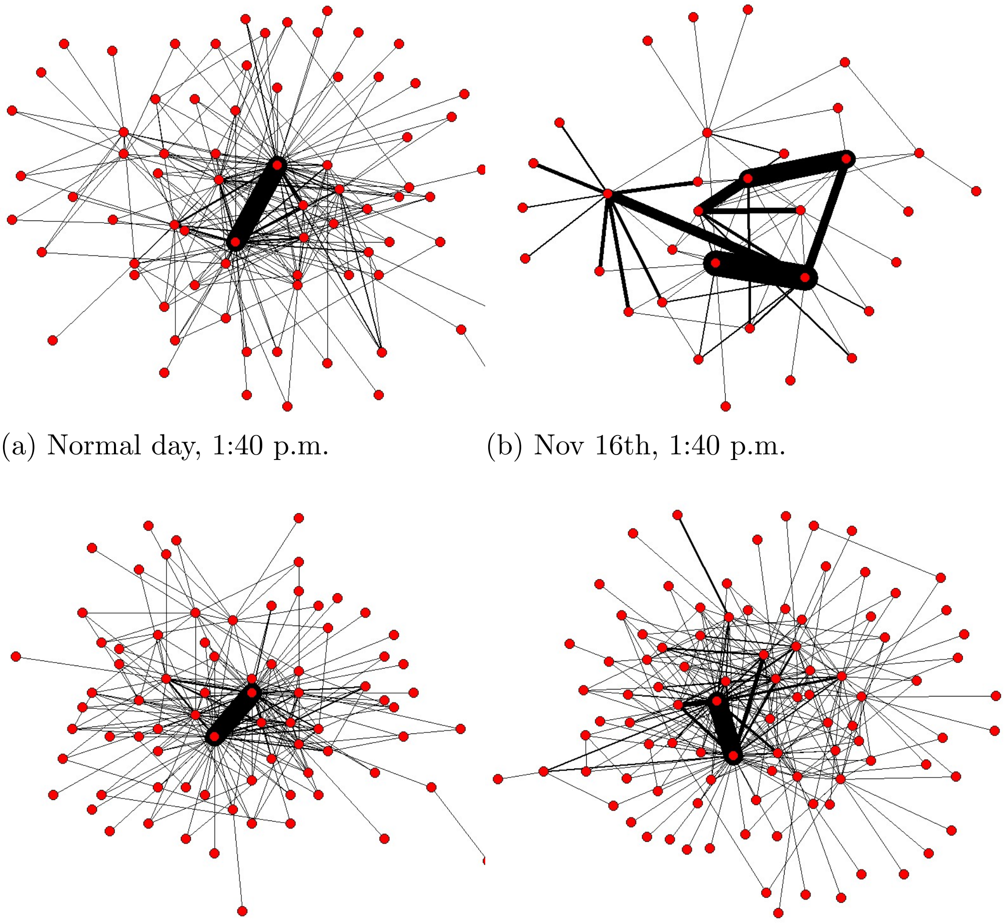
3.5.1 Operational disruption of the system

On Thursday November 16th 2006 the Danish large-value payment system experienced an intraday operational failure, cf. Danmarks Nationalbank (2007). The system opened as usual, but due to an unsuccessful software update the settlement process stopped after the first few minutes and the system remained down for more than 6 hours. When the system came up again later that day, a large bulk of transactions was settled immediately.

As a consequence of this event, the Danish central bank extended the closing of the system with 15 minutes but only two transactions took place after the official closing time at 3:30 p.m. Furthermore, the central bank provided extra liquidity to the market by repurchases of certificates of deposit.

[12]Event studies are useful to analyze whether banks change behaviour and if this benefits the functioning of a network. Both the subprime crisis in 2007 and effects from Sept. 11th, 2001 had substantial influence on the network topology of the US financial market, cf. Soramäki et al. (2007) and Kroszner (2007). The Danish payments and money market networks were unaffected by the subprime crisis in a data set for the period July-September 2007. Pröpper et al. (2008) reach the same conclusion in a similar study for credit markets in the Netherlands.

Figure 3.10: Operational disruption in the payments network



(a) Normal day, 1:40 p.m.

(b) Nov 16th, 1:40 p.m.

(c) Normal day, End of day

(d) Nov 16th, End of day

Note: The figures are weighted by value.

The operational disturbance implied a different structure of the networks during the day, cf. figure 3.10 and 3.11 and table 3.6. By the end of the day, almost all of the topological measures were significantly different from the 2006 average, cf. table 3.6. The activity and size of the payments network decreased significantly. The average path length had decreased significantly by the end of the day, whereas the connectivity and clustering of the payments network increased significantly. That is, the payments network became narrower.

In opposition to this, the activity in terms of volume and the size of the money market increased although the average value of each money market loan had decreased significantly by the end of the day. The connectivity of the money market network decreased significantly, whereas the average path length and average node degree increased. Thus, although the actual number of links out of the potential number of links decreased, the average number of links per active bank increased in the money market. All in all, the money market became wider during this event.

The drop in payments network activity and boom in overnight money market loans are in opposition to the seasonal effects by the turn of the month, cf. table B.1 and B.2.

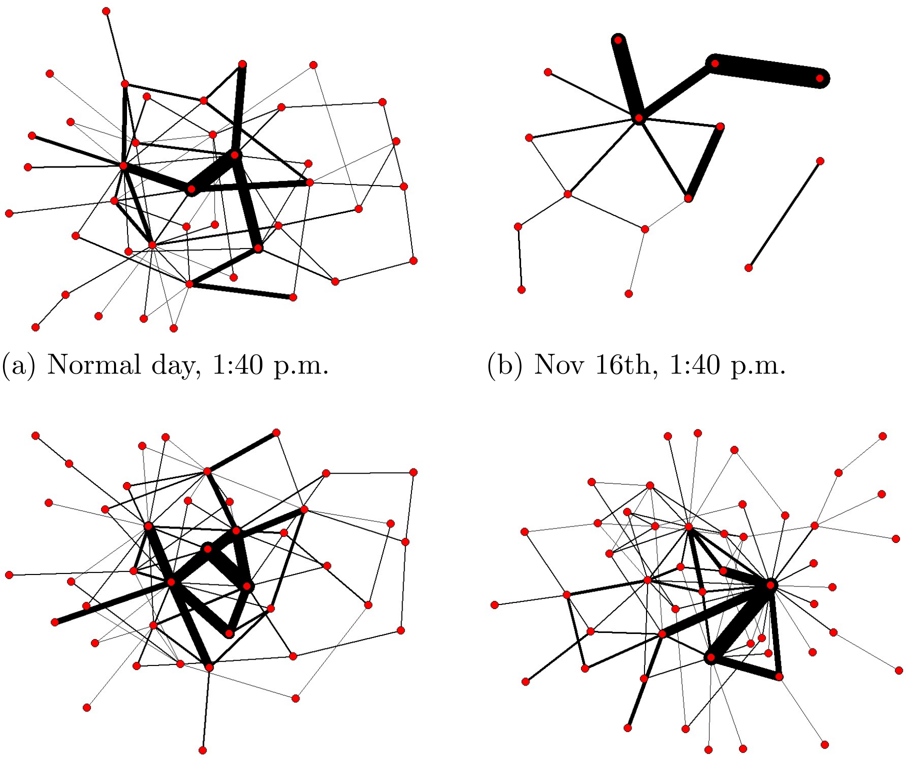
Although the operational disruption of the system had a large impact on the topologies of the payments and the money market networks, these effects were temporary. If the operational event had lasted longer, these effects might have

Table 3.6: Effects of an operational breakdown in the networks

	2006	Confidence limits		Operational breakdown	
	Average	Lower	Upper	End of day	1:40 p.m.
Payments					
Volume	2,162.4	2,127.1	2,197.6	**1,883.0**	**220.0**
Value, billion DKK	105.5	102.2	108.9	**80.6**	**6.7**
Nodes	59.1	58.4	59.8	**55.0**	**33.0**
Links	282.6	277.5	287.7	**260.0**	**70.0**
Connectivity, per cent	8.3	8.2	8.4	**8.8**	**6.6**
Clustering	0.53	0.53	0.54	**0.55**	**0.27**
Average path length	2.48	2.47	2.49	**2.46**	**1.75**
Average node degree	4.77	4.73	4.81	4.73	**2.12**
Money market					
Volume	86.4	83.2	89.7	**103.0**	**19.0**
Value, billion DKK	22.9	21.9	23.9	**20.9**	**3.5**
Nodes	27.4	26.6	28.3	**29.0**	**15.0**
Links	75.0	72.1	77.9	**82.0**	**16.0**
Connectivity, per cent	11.2	10.5	11.9	**10.1**	**7.6**
Clustering	0.17	0.16	0.18	0.18	**0.08**
Average path length	2.94	2.90	2.99	**3.01**	**0.54**
Average node degree	2.69	2.64	2.73	**2.83**	**1.07**

Note: Mean values of selected summary statistics for the core. Confidence limits for the 95 per cent confidence interval are used to determine the significant variables, which are bold. Clustering, average path length and average node degree are reported with 2 decimals.

Figure 3.11: Operational disruption in the money market network



(a) Normal day, 1:40 p.m.

(b) Nov 16th, 1:40 p.m.

(c) Normal day, End of day

(d) Nov 16th, End of day

Note: The figures are weighted by value.

been even more pronounced.

3.5.2 Payment disruption by a major participant

One of the largest commercial banks in Denmark, Danske Bank, was not able to send payments in the large-value payment system on two successive days in March 2003. This was caused by a major it-problem[13]. The Danish central bank supplied the banks with extra liquidity to overcome a potential lack of liquidity in the markets as the major participant was able to receive, but could not send transactions to other banks.

The effects on the networks' structures were most pronounced on the first day of

[13] For a description of this event see Berlingske (2003a, 2003b).

the event, Wednesday March 12th. The activity and size of the payments network decreased, whereas the activity in terms of volume and the size of the money market network increased by around 50 per cent on this day although the average size of an overnight money market loan decreased cf. table 3.7. Connectivity and clustering increased significantly in the payments network, whereas the average path length and the average node degree decreased. In the money market, the effects on these four variables were opposite.

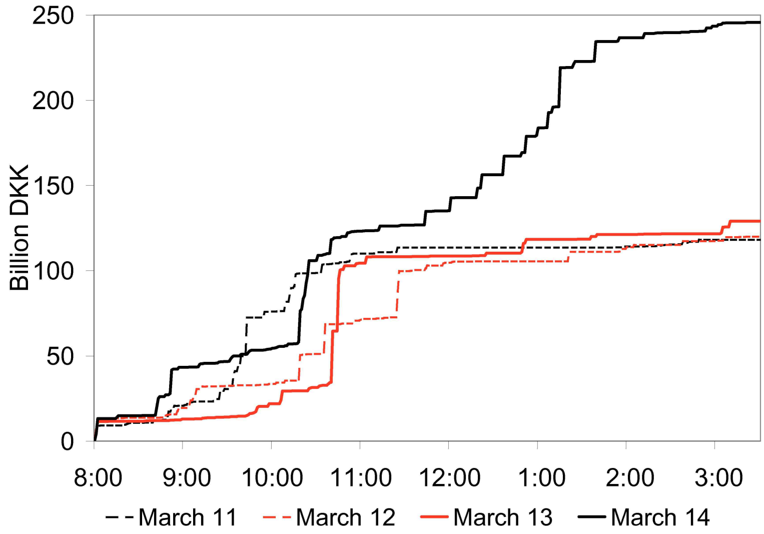
Table 3.7: Effects of payment disruptions by a major participant

	Average	Confidence limits			
	March 2003	Lower	Upper	March 12	March 13
Payments					
Volume	2,306.5	2,267.4	2,345.6	**1,505.0**	**1,625.0**
Value	145.8	142.1	149.5	**119.7**	**128.6**
Nodes	56.5	55.9	57.2	**49.0**	**58.0**
Links	281.2	275.8	286.5	**227.0**	**254.0**
Connectivity, per cent	9.0	8.9	9.1	**9.7**	**7.7**
Clustering	0.50	0.50	0.51	**0.58**	**0.43**
Average path length	2.46	2.45	2.47	**2.44**	**2.57**
Average node degree	4.95	4.91	4.99	**4.63**	**4.38**
Money market					
Volume	64.4	61.3	67.5	**92.0**	**46.0**
Value	18.7	17.8	19.6	**8.8**	**7.8**
Nodes	24.1	23.0	25.1	**37.0**	**19.0**
Links	56.9	54.2	59.7	**87.0**	**44.0**
Connectivity, per cent	12.8	11.7	13.9	**6.5**	12.9
Clustering	0.17	0.16	0.18	**0.10**	0.17
Average path length	3.03	2.97	3.09	**3.70**	**2.96**
Average node degree	2.24	2.19	2.28	**2.35**	**2.32**

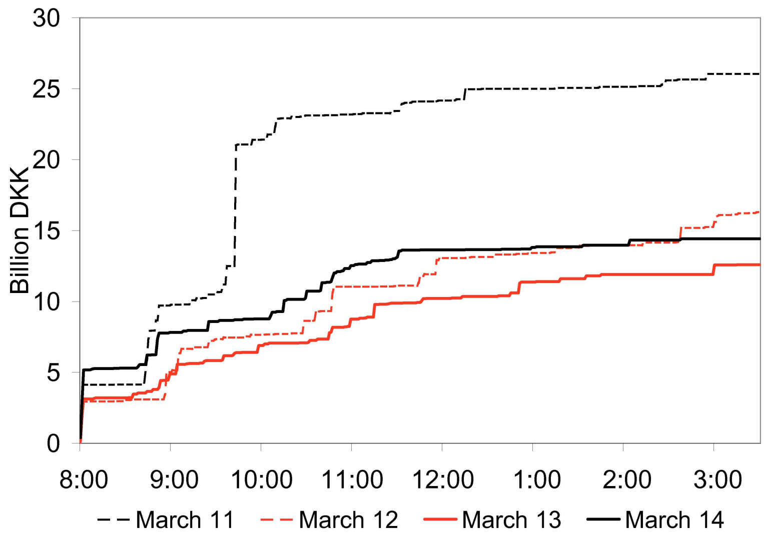
Note: The note to table 6 also applies here. The average of March 2003 excludes data from March 12th and March 13th.

On the second day of this event, the major participant informed the public about the it-problem and its implications for the bank's business. Together with the significant boom in activity and size of the money market of the first day of payment disruptions by a major participant, this lead to a decrease in activity and size of the money market network on the second day of this event. This decreased the average path length and average node degree.

Figure 3.12: Payment disruption by a large bank



(a) Payments



(b) Money market

Note: Amounts settled in the networks during the day on selected dates in March 2003. March 11th (March 14th) was the last (first) business day before (after) the payment disruption by a major participant, while this event had effect on March 12th and 13th. The value of overnight loans in the money market increase by coincidence on March 11 as there are no holiday effects or effects of additional liquidity adjustments by the central bank this day. The opening time of the large value payment system was 8.00 a.m.-3.30 p.m. until June 1st 2003.

The activity and the size in terms of links of the payments network remained significantly lower than the average for March 2003, but more banks became active in the payments network on the second day of payment disruptions. This is reflected in the significant drop in connectivity, clustering and average node degree. The average path length increased, i.e. transactions had to pass more links to reach the final recipient of a transaction.

The disruptions by a major participant also caused an accumulated settlement demand in the payments network and this lead to a sharp increase in the value settled within this network on the first normal business day after the event, cf. figure 3.12.

Compared with the operational breakdown, the effects of payment disruptions by a major participant are larger in both networks. The structural changes in the networks' topologies were temporary. And it seems as if the other banks took precautionary actions towards the disturbance and continued settlements as far as possible in both networks.

3.6 Conclusion

The topological analysis shows that the structure of the Danish money market is different from the structure of the payments network. This is a consequence of the difference in the nature of transactions in the networks. Transactions in the money market network are driven by banks' behaviour whereas transactions in the payments network arise from banks' proprietary transactions as well as customer driven transactions. In the payments network, two commercial banks are responsible for a rather large share of the total activity, whereas the banks in the core of the money market are of more equal size. Both networks are rather concentrated.

Our results show that the distribution of in- and out-degrees follow the exponential or the negative binomial distributions in the payments network, while the exponential distribution captures the distribution of in- and out-degrees quite well in the money market. In other countries, in- and out-degrees follow power-law distributions, but power-law distributions are clearly rejected in our data set.

We find clear evidence of seasonal effects for both networks. The results show that the payments network becomes wider by the turn of the month and quarter and on the first business day following a holiday. In contrast to this, weekday effects drive the calendar effects observed in the money market.

Event studies of an operational disruption imply a different structure of the networks during the day. Although the structure of the networks is almost normal by the end of the day, the daily activity of the payments network decreased considerably. In contrast to this, the daily activity of the money market increased. The topological effects of this event are in line with the seasonal effects by the turn of the month but with the opposite signs. The effects of the operational event were temporary, but might have been more pronounced in case the operational event had lasted longer than it did. Payment disruptions by a major participant decreases (increases) the level of activity in the payments (money market) network; especially on the first day of the event. An accumulated settlement demand was build up in the payments network, which was released on the first normal business day after the payment disruption by a major participant leading to a sharp increase in the value settled in the payments network.

It could be interesting to see if the payments network builds up in a different way than the money market network during the day. At the moment a rather large fraction of the settlements take place before noon both in the money market and in the payments network, but the effects of a different timing of settlements on the structure of the networks is a question for further research.

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3.8 Appendix A: More summary statistics

Table A.1: More summary statistics, payments and money market networks, 2006

	Mean	Median	Min	Max	Std	Mean
Payments						Fedwire
Distance measures						
Diameter	5.5	5.0	4.0	8.0	0.7	6.6
MDF, M(2)	54.6	54.8	44.7	65.4	4.2	41.6
MDF, M(3)	91.2	91.4	83.2	97.8	2.7	95.9
MDF, M(4)	99.1	99.3	94.9	100.0	0.8	99.9
MDF, M(5)	99.9	100.0	96.9	100.0	0.3	n.a.
Degree distribution						
max k^{in}	34.6	34.0	24.0	51.0	4.4	2,097.0
max k^{out}	29.0	29.0	22.0	53.0	3.9	1,922.0
Centrality measures						
Betweenness, links	30.3	30.3	20.7	38.4	3.7	n.a.
Betweenness, nodes	86.0	85.8	61.9	125.4	10.5	n.a.
						Fed Funds
Money market						Market
Distance measures						
Diameter	6.7	7.0	2.0	10.0	1.3	7.3
MDF, M(2)	42.1	40.6	26.6	100.0	9.5	n.a.
MDF, M(3)	71.6	71.4	47.3	100.0	10.0	n.a.
MDF, M(4)	89.7	91.0	61.6	100.0	7.3	n.a.
MDF, M(5)	96.6	98.0	71.7	100.0	4.2	n.a.
MDF, M(6)	98.9	99.9	82.0	100.0	2.3	n.a.
MDF, M(7)	99.7	100.0	90.1	100.0	1.1	n.a.
Degree distribution						
max k^{in}	10.3	10.0	2.0	24.0	3.6	127.6
max k^{out}	10.3	10.0	2.0	21.0	3.4	48.8
Centrality measures						
Betweenness, links	29.2	29.4	2.0	51.1	8.4	n.a.
Betweenness, nodes	52.1	52.5	0.7	92.6	16.5	n.a.

Note: The data reported refer to the core. The Mass Distribution Functions, MDF, are estimated based on payments submitted from a node. max k^{in}(max k^{out}) is the maximum number of links ending in (starting from) a node. Data for the Fedwire and the Fed Funds Market are from Soramäki et al. (2007) and Bech and Atalay (2008). n.a. means not available.

Table A.2: Summary statistics for the transactions network, 2006

	Mean	Median	Min	Max	Std
Basic network properties					
Volume	2,355.9	2,337.5	1,607.0	4,171.0	323.6
Value	131.7	128.9	46.9	224.8	30.8
Nodes	67.8	67.0	57.0	88.0	4.8
Links	373.7	368.0	283.0	713.0	48.4
Connectivity, per cent	8.3	8.2	6.8	10.1	0.7
Reciprocity, per cent	24.0	24.0	19.1	28.4	1.9
Clustering	0.5	0.5	0.4	0.6	0.0
Average path length	2.4	2.4	2.2	2.6	0.1
Average node degree, k	5.5	5.5	4.6	8.1	0.4
Link weight, value	0.4	0.4	0.1	0.6	0.1
Link weight, volume	6.3	6.3	4.3	8.7	0.6
Node strength, value	1.9	1.9	0.8	3.4	0.5
Node strength, volume	34.7	34.4	23.0	48.8	3.9
Distance measures					
Diameter	5.1	5.0	4.0	8.0	0.6
MDF, M(2)	58.1	58.1	48.7	69.8	4.2
MDF, M(3)	94.3	94.4	87.1	98.8	2.1
MDF, M(4)	99.7	99.8	96.4	100.0	0.5
MDF, M(5)	100.0	100.0	98.1	100.0	0.1
Degree distribution					
max k^{in}	40.8	40.0	31.0	57.0	4.7
max k^{out}	34.5	34.0	24.0	54.0	4.2
Centrality measures					
Betweenness, links	29.4	29.0	22.5	38.0	3.2
Betweenness, nodes	93.9	93.5	74.3	121.0	9.1

Note: The transactions network is the network based on the full data set. The notes to table 3.4 and table A.1 also apply to this table.

3.9 Appendix B: Seasonal effects

Estimations of seasonal effects in the payments and the money market networks are based on data for the core of these networks.

Holiday effects are measured on the first business day following a closing day. American holidays are holidays in addition to Danish holidays. European holidays are captured by the dummies for Danish holidays and turn of month. The turn of month (quarter) includes the first and the last opening day in each month (quarter).

Table B.1: Seasonal effects, payments network, 2006

	Nodes	Links	Value	Volume	Aver. node degree	Con-necti-vity	Aver. path length	Clu-ste-ring
Intercept	59.9**	279.2**	95.1**	2.2**	4.7**	8.0**	2.50**	53.7**
	0.8	4.8	3.2	0.0	0.0	0.1	0.01	0.6
Danish holidays	5.7*	73.9**	23.8**	0.6*	0.7**	0.3	-0.08	2.6
	2.4	15.4	8.9	0.3	0.2	0.5	0.06	2.3
US holidays	1.1	18.5*	15.9*	0.4**	0.2**	0.2	-0.05*	2.6
	1.4	6.9	6.9	0.1	0.1	0.3	0.02	1.9
End of Quarter	17.1**	146.3**	43.2**	0.7**	0.9**	-0.8*	-0.01	-1.1
	2.2	10.0	8.8	0.1	0.1	0.4	0.03	2.3
End of Month	6.1**	48.5**	22.0**	0.2*	0.3**	-0.3	-0.01	0.3
	1.2	7.0	6.8	0.1	0.1	0.2	0.02	1.2
Expected liquidity adj.	2.5*	18.1**	5.4	0.2**	0.1*	-0.2	0.00	1.7*
	1.3	7.1	6.1	0.1	0.1	0.2	0.02	0.9
Unexpected liquidity adj.	1.7	24.6*	0.5	0.1	0.3**	0.2	-0.04**	1.7
	1.5	10.6	7.9	0.1	0.1	0.2	0.01	2.3
Monday	-3.6**	-13.2*	6.1	-0.2**	0.1	0.6**	-0.03*	0.3
	1.1	6.9	6.4	0.1	0.1	0.2	0.02	1.1
Tuesday	-1.4	-13.4*	-2.5	-0.2**	-0.1*	0.0	0.03*	-0.2
	1.1	5.6	4.8	0.1	0.0	0.2	0.02	0.9
Thursday	-1.9*	-5.2	0.7	-0.1*	0.1	0.4*	-0.02	0.8
	1.1	6.4	5.0	0.1	0.1	0.2	0.02	0.9
Friday	2.8*	38.7**	22.9**	0.0	0.4**	0.2	0.00	-4.4**
	1.3	11.4	4.8	0.1	0.1	0.2	0.01	0.9
R^2	31.9	40.7	20.8	26.7	34.6	9.5	7.8	17.2

Note: For each explanatory variable, the first line of results is parameter estimates and the second robust standard errors. Significant parameters on a 1 (5) per cent level is marked with ** (*) in a one-tailed t-test (df=200). Value is in billion DKK, volume in thousands and connectivity and clustering in per cent. Average path length is reported with two decimals.

We also test for effects of liquidity adjustments by the central bank. The Danish central bank adjusts liquidity in addition to the regular adjustments on Fridays on days with ingoing tax payments or outgoing social benefits etc. Additional adjustments will normally be announced in advance (expected liquidity adjustments), but a few adjustments are not announced (unexpected liquidity adjustments).

Table B.2: Seasonal effects, money market network, 2006

	Nodes	Links	Value	Volume	Aver. node degree	Con- necti- vity	Aver. path length	Clu- ste- ring
Intercept	30.6**	84.1**	24.4**	0.1**	2.7**	9.2**	3.05**	15.4**
	0.8	2.9	1.1	0.0	0.0	0.4	0.05	1.1
Danish holidays	-4.7	-12.4	-3.4	0.0	-0.3	10.6	-0.35	-2.6
	4.2	13.3	4.3	0.0	0.2	7.6	0.26	3.3
US holidays	1.5	5.3	2.8	0.0	0.1	-1.2	-0.11	3.8
	1.5	6.1	3.7	0.0	0.1	1.3	0.10	3.7
End of Quarter	-2.1	2.5	-3.6	0.0	0.4**	2.3*	-0.16	1.4
	1.8	6.9	2.2	0.0	0.1	1.1	0.11	2.1
End of Month	-5.0**	-14.9**	2.2	0.0**	-0.1	4.1*	-0.12	0.3
	1.3	4.0	2.4	0.0	0.1	2.5	0.13	2.3
Expected liquidity adj.	-0.9	0.1	-1.0	0.0	0.1	0.4	-0.09	2.4
	1.3	4.7	1.4	0.0	0.1	0.7	0.07	2.0
Unexpected liquidity adj.	3.1	14.8	-1.7	0.0	0.2*	0.7	-0.16**	2.1
	3.5	12.0	2.1	0.0	0.1	2.0	0.05	2.4
Monday	-5.8**	-18.9**	-4.2**	0.0**	-0.1*	2.8**	-0.10	1.1
	1.2	4.2	1.5	0.0	0.1	1.0	0.07	1.6
Tuesday	-3.6**	-9.6*	-1.7	0.0*	0.0	2.3*	-0.12	1.7
	1.2	4.2	1.6	0.0	0.1	1.4	0.07	1.6
Thursday	0.5	1.8	1.1	0.0	0.0	0.0	-0.03	2.2
	1.1	4.1	1.5	0.0	0.1	0.5	0.06	1.7
Friday	-5.6**	-17.4**	-2.7	0.0**	-0.1	2.3**	-0.12*	2.4
	1.2	4.0	1.5	0.0	0.1	0.7	0.06	1.6
R^2	22.6	18.6	7.8	17.6	8.6	17.3	6.9	2.8

Note: The note to table B.1 also applies to this table.

3.10 Appendix C: The Furfine algorithm

The Furfine algorithm is used to identify overnight money market loans in order to split our data set into transactions stemming from two economically different networks.

The algorithm defines a transaction as an overnight money market loan if 1) the borrowed amount is at least 1 million DKK in integer numbers, 2) the borrowed amount is repaid with interest the next business day and 3) the interest amount is within an acceptable range, $i = [i_{Low}, i_{High}]$. The lower (upper) bound of this interval is the minimum interest rates on unsecured overnight lending reported by a panel of Danish banks minus (plus) 25 basis points. The acceptance range is extended with ± 25 basis points since "interest rates charged are likely to vary across transactions", cf. Furfine (1999, p. 26). The acceptance range on Danish data is smaller than the ± 50 basis points Furfine (1999) uses on Fedwire transactions. But broadening (decreasing) the acceptance range to ± 50 basis points (± 0 basis points) on Danish data gives almost the same classification of unsecured overnight lending by the algorithm.

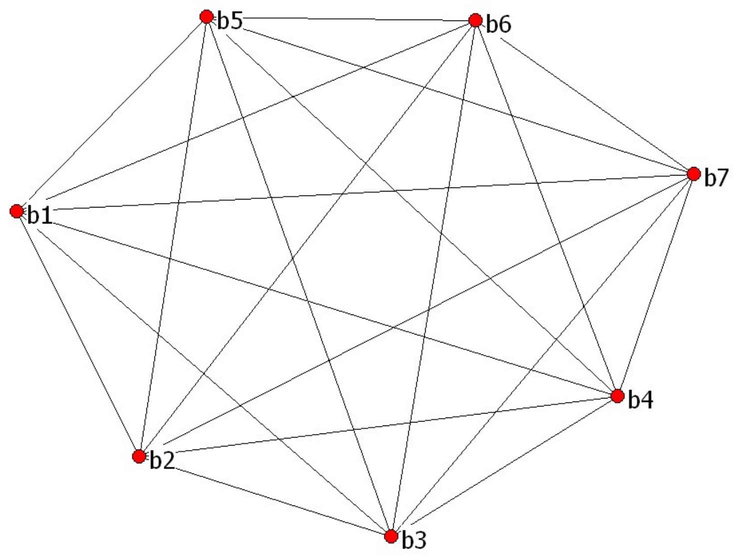
3.11 Appendix D: Stylized networks and statistical measures used

Two different extremes of stylized networks are illustrated in figure D.1. In a complete network, a bank has links to all other banks in the network such that each bank submits and receives transactions to/from all other banks within the network. In a tree network bank 1 submits transactions to bank 2 and 3, which submits transactions to bank 4 and 5 respectively bank 6-7.

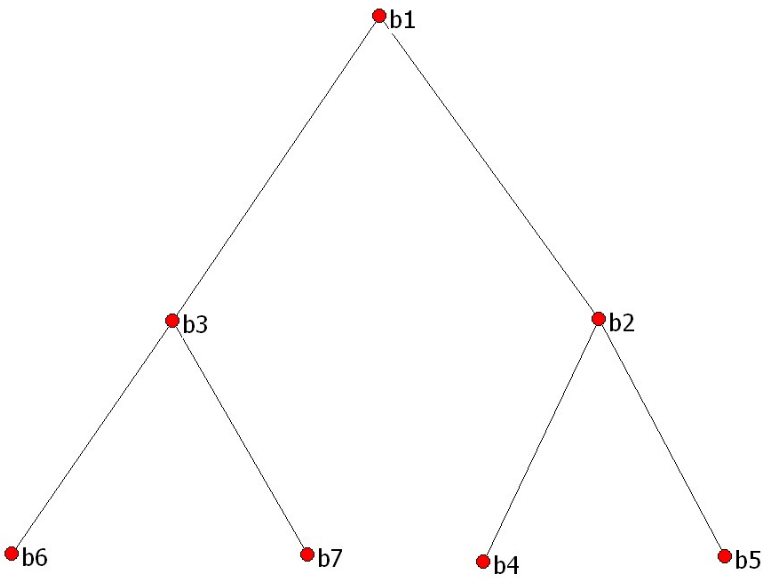
Another type is random networks, which is constructed by adding links at random to a given set of nodes. Stylized networks are not observed empirically but they are useful as benchmarks for analytical purposes.

Table D.1 gives a short description of the statistical measures used in the same order as these measures appear in the paper.

Figure D.1: Stylized networks



(a) Complete network



(b) Tree network

Table D.1: List of topological measures used

Variable	**Description**
Average node degree	A measure of the average number of links per node, $k = \frac{1}{n}\sum_{i=1}^{n} k_i^{in} = \frac{1}{n}\sum_{i=1}^{n} k_i^{out} = \frac{m}{n}$, where $\sum_{i=1}^{n} k_i^{in}(\sum_{i=1}^{n} k_i^{out})$ is the sum of links that terminate in (originate from) a node.
Average path length	The average path length for a network measures the number of links a transaction must pass to reach another bank in the network. Formally, $l = \frac{1}{n}\sum_{i=1}^{n} l_i$, where l_i is the average path length of node i given by $l_i = \frac{1}{n-1}\sum_{j\neq i}^{n-1} d_{ij}$ where the distance d_{ij} between node i and j is 1 if node i has a link to node j. The average path length is estimated from payments submitted from a node in this paper, but it is also possible to compile this measure from payments received in a node.
Betweenness (for nodes or links)	Betweenness is a centrality measure, where the idea is that node i (link ij) is more central, the more paths between nodes that run via node i (run via link ij) in the network.
Connectivity	Connectivity, p, is given by $p = \frac{m}{n(n-1)}$, where n is the number of nodes and m the number of links in a network, e.g. the ratio of actual links formed to the number of potential links. p is a measure of the degree of completeness of a network and it varies between $\frac{1}{n}$ (tree network) and 1 (complete network).

Continued on next page

Table D.1 List of topological measures used – Continued

Variable	**Description**
Clustering	Clustering is the probability that two banks, where each of them has a link to bank i, also have a link to each other. The clustering coefficient of node i is $C_i = \frac{(m_{nn,i})}{k_i(k_i-1)}$ where $m_{nn,i}$ is the number of links between the neighbors of node i and k_i is the number of payments terminating in (or originating from) node i. In other words, clustering measures the actual number of links to the potential number of links between the neighbor-nodes of node i, e.g. clustering varies between 0 (tree network) and 1 (complete network). The clustering coefficient for the whole network is $C = \frac{1}{n}\sum_{i=1}^{n} C_i$. The clustering coefficient is equal to the connectivity of the network, $C = p$ in a random network where the links between banks are distributed randomly. Clustering can be estimated using either the payments reviced in a node or payments submitted from a node. The latter measure is used here.
Diameter	The maximum distance between two nodes in a network. Defined as $D = max_i(max_j d_{ij})$.
Link weight	Links can be weighted by either the volume or value of payments through a link, e.g. a link, which handles 10 transactions, is more important than a link, which handles 1 transaction and vice versa for links weighted by values transferred. Formally, the w_{ij} is the weigth assigned to the link between node i and j.
Mass Distribution Function, MDF(x)	x is the distance from a node. That is, MDF(2) says how large a share of all the nodes in the network, which can be reached within the distance 2 from a node. Formally, $M(x) = \frac{1}{n(n-1)}\sum_{i=1}^{n}\sum_{i\neq j} 1(d_{ij} \leq x)$, where $1(\cdot)$ has the value 1 if $d_{ij} \leq x$ and 0 otherwise. The mass distribution function can be estimated using payments submitted to or received from the nodes in a network. The MDF(x)-measures in this paper are based on payments submitted from a node.

Continued on next page

Table D.1 List of topological measures used – Continued

Variable	**Description**
Maximum in-degree of a node, max k^{in}	This is a measure of the maximum number of links that terminate in a node. Similarly, the maximum out-degree of a node, max k^{out}, measures the maximum number of links that originate from a node.
Node strength	Node strength for node i is defined as $s_i^{out} = \sum_{j=1}^{n} w_{ij}^{out}$ for payments submitted from a node (we use this measure in this paper) or $s_i^{in} = \sum_{j=1}^{n} w_{ij}^{in}$ for payments received in a node. That is, the larger the strength of a node is, the more important is the node in the network.
Reciprocity	Reciprocity measures the share of links for which there is a link in the opposite direction (per cent). Varies between 0 (tree network) and 1 (complete network).

Chapter 2

Competition from Settlement Banks in RTGS-systems: The Case of Indirect Settlement

I thank professor Thomas Rønde for valuable comments and suggestions during the preparations of this paper. Helpful comments were also provided by Tuomas Takalo, Michala Ehlers Rasmussen and Lars Jul Overby. This paper has benefited from comments by participants in the Nordic Finance Network Workshop 2008 and by seminar participants at the Department of Economics, University of Copenhagen, Danmarks Nationalbank, Bank of Finland and Helsinki Center for Economic Research (HECER), Finland. The views expressed do not necessarily reflect the views of Danmarks Nationalbank.

Abstract

This paper presents a model where a payment system, a RTGS-system, competes against a settlement bank on offering settlement services to two large and two small banks. The settlement bank acts as intermediary between members and non-members of the payment system. The costs of settlement determine whether the banks settle *directly* within the RTGS-system or *indirectly* via the settlement bank.

There are three market equilibria; 1) all banks settle indirectly via the settlement bank, 2) all banks settle directly within the RTGS-system or 3) large banks with many transactions settle directly and small banks settle indirectly. However, there are only two possible market equilibria, 1) and 2), when the settlement bank obtains a higher profit in 1) than in 3).

The market solution differs from the social planner's solution. This inefficiency is driven by the different settlement costs within the settlement systems. An efficient market solution can be reached with a welfare-maximizing RTGS-system.

The model is extended by risk of illiquidity for the banks and the settlement bank. This implies that they can be unable to settle payments and that the market solution changes. Two additional situations can arise in the market solution. First, for a high risk of illiquidity, 2) and 3) are the only equilibria. That is, the settlement bank does not serve large banks. In the second situation, there is only one equilibrium, namely 4) large banks settle indirectly and the small banks settle within the payment system. Despite of these changes, the market solution is still inefficient in the sense that it differs from the social planner's solution.

Version: April 2010

Keywords: Banks, Payment System, Indirect Settlement, Correspondent banking, Tiering.

JEL classification: E42, G21

Introduction

In recent years, agents in financial markets have become more and more interconnected via cross-holdings in a wide range of different financial products such as derivatives, foreign exchange trades or hedging against risk stemming from fluctuating interest rates, exchange rates and credit defaults. Many of these trades are settled within payment systems. Nevertheless, some trades are settled on the books of a settlement bank as the payment systems have limited reach.

This is due to different design of the world's payment systems with respect to 1) the type of financial transaction, e.g. trades of shares and securities, foreign exchange trades, retail payments or interbank payments, 2) different terms of settlement, e.g. settlement currency, opening hours, costs of settlement (membership fees, fees per transaction etc.) and 3) national regulation of banking activities. To overcome some of these difficulties, a European Real-Time Gross Settlement (RTGS) System for interbank payments in euro (Target2) and a settlement system for foreign exchange trades in 15 currencies, Continuous Linked Settlement (CLS), have been developed in recent years.

The main advantage from indirect settlement of trades is that it enables banks to submit payments no matter if the recipient bank is member of the same payment system as the submitting bank. Indirect settlement can also intensify the competition for settlement service resulting in improved settlement services or lower costs of settlement.

In this paper, we define settlement of payments within a payment system as *direct settlement,* since a bank submits payments directly to its recipients, and *indirect settlement*[1] as payments submitted via a settlement bank. A settlement bank is a bank, which provides settlement services to other banks. That is, it acts as intermediary between members and non-members of a payment system.

We build a model where a payment system, a RTGS-system, competes against a settlement bank on offering settlement services to two large and two small banks. All banks can settle indirectly via the settlement bank. Both the payment system and

[1]The term indirect settlement is used throughout this paper. Correspondent banking or tiering are other frequently used terms. Tiering implies a limited number of member banks of a payment system. This necessitates that some of the member banks act as settlement banks to facilitate indirect settlement with non-member banks. The CHAPS Sterling and CHAPS Euro payment systems in the UK are examples of tiered payment systems, but tiering within payment systems exist to some degree in a number of countries, cf. Harrison et al. (2005) and BIS (2003). Banks, which settle indirectly, may be known formally by the network owner. This is the case in Norway where a commercial bank acts as settlement bank on behalf of several small banks, which are formally known by the network owner, cf. BIS (2005) and Norges Bank (2008).

the settlement bank maximize profits. There is sequential price setting such that the RTGS-system sets its price before the settlement bank does.

The model in this paper provides a new approach towards the analysis of indirect settlements. Competition between settlement institutions is assumed away in Lai et al. (2006) and Adams et al. (2008). In these papers, a fraction of the payments is settled indirectly by assumption. Moreover, only small banks choose between direct and indirect settlement and the payment system is not modelled explicitly in Chapman et al. (2008). As described above, all banks can settle indirectly and the payment system is modelled as a RTGS-system in the current paper.

The banks are required to choose either direct settlement via the payment system or indirect settlement via the settlement bank. Bilateral netting between banks is assumed away here. The banks' choice of settlement institution depends on the costs of settlement within the RTGS-system and the settlement bank. The costs from settlement in the RTGS-system include a membership fee and a fee per transaction. There are set-up costs related to the use of the RTGS-system, but no fixed costs to access the settlement bank. Thus, the cost of settlements within the settlement bank is a fee per transaction. The cost structure implies that large banks with a huge number of transactions tend to prefer a fixed fee and a low fee per transaction, i.e. large banks tend to prefer the RTGS-system. By the same logic, small banks tend to prefer the settlement bank.

The results show that three market equilibria can arise; 1) all banks settle indirectly via the settlement bank, 2) all banks settle directly within the RTGS-system or 3) large banks, which have many transactions, settle directly and small banks with few transactions settle indirectly. However, there are only two possible market equilibria, 1) and 2), when the settlement bank obtains a higher profit in 1) than in 3).

The market solution is inefficient in the sense that it differs from the social planner's solution. This is driven by different cost structures within the settlement systems, which works as a kind of product differentiation. Thus, the RTGS-system and the settlement bank can price above or equal to marginal costs depending on how many banks they serve with settlement services. The inefficiency is reduced with a cost-covering RTGS-system. A fully efficient market solution is reached with a welfare-maximizing RTGS-system.

The model is extended by risk of illiquidity for the banks and the settlement bank. This implies that they can be unable to settle payments. Compared with the market solution of the basic model, two additional situations can arise. First, for a high risk of illiquidity, 2) and 3) are the only equilibria. That is, the settlement bank does not serve large banks. In the second situation, there is only one equilibrium, namely 4) large banks settle indirectly and the small banks settle within the payment system. The market solution differs from the social planner's solution and this is in line with the findings in the basic model.

The rest of this paper is organized as follows. We discuss related literature in section 4.1. We introduce the model in section 4.2 and solve for the market equilibrium in section 4.3. Section 4.4 compares the market solution with the welfare optimal outcome of the model. Section 4.5 considers the assumption of a balanced payment flow between banks and the timing of the price setting by the RTGS-system and the settlement bank. The results for the model extended with illiquidity risk are in section 4.6, but the details are provided in the appendix. Finally, section 4.7 concludes.

4.1 Review of the literature

The model in this paper aims at analyzing the effects of indirect settlement in a theoretical framework, where the incentives of banks and settlement networks play a crucial role. The banks can demand settlement services from two different networks (the RTGS-system and the settlement bank), which compete against each other. This is a new approach towards the analysis of indirect settlements. Previous studies include the models in Lai et al. (2006), Adams et al. (2008) and Chapman et al. (2008). Lai et al. (2006) model a tiered payment system, where some banks settle directly via a payment system owned by a central bank and some banks settle indirectly via a settlement bank. They focus on the credit risks imposed on the settlement bank in equilibrium as the settlement bank provides credit to the banks settling indirectly. Adams et al. (2008) consider a physical network model of a tiered payment system, i.e. they consider a number of banks and transactions between these banks. They calibrate the model with data from the UK CHAPS system in order to analyze how the structure of the tiered network changes for different parameter values. Both in Lai et al. (2006) and in Adams et al. (2008) a fraction of payments is settled indirectly by assumption. Thus, competition between payment systems, which plays a central role in this paper, is assumed away. Furthermore, the welfare optimal outcome is not considered.

Chapman et al. (2008) let small agents choose between direct and indirect settlement depending on the costs of settlement, whereas large agents choose between direct settlement or acting as a settlement bank. The settlement system is not modelled explicitly. The model in this paper allows all banks to settle indirectly and effects from indirect settlement within a RTGS-system are considered.

As already mentioned, banks choose between direct settlement within a RTGS-system and indirect settlement via a settlement bank, which functions as a net settlement system[2]. In a gross settlement system banks pay the gross amount of each payment so the banks' liquidity costs are quite high, but the benefit is the immediate settlement of payments. Payments in a net settlement system are netted out before they are settled. This implies low liquidity costs, but the counterparty risks can be substantial as banks in a netting system may build up large positions on each other during the day. This basic trade-off has been analyzed by Kahn and Roberds (1998) and Kahn et al. (2003).

As discussed above, banks' possibilities to become members of a payment system have implications for the volume of indirect settlements. Holt- hausen and Rønde (2002) analyse a case where a national regulator must decide on foreign banks' access to a national large-value payment system (LVPS). They show that this choice depends on the limited information about foreign banks available to the national regulator.

The price scheme does also affect the demand for indirect settlement. Holthausen and Rochet (2006) analyze the optimal price scheme in public and private LVPS with full cost recovery. The private LVPS has low marginal costs as it only serves banks with a high volume of transactions whereas marginal costs within the public LVPS are higher as this system serves banks with different transactions volume. They show that the public LVPS is attractive to all banks if it price differentiates between banks, e.g. the marginal price must be lower than marginal costs to attract banks with many transactions and all banks must pay a fixed fee in order to ensure full recovery of costs in the public LVPS. This feature is also incorporated in this paper as there is a fixed and a variable fee within the payment system and a variable fee within the settlement bank.

Extending the model in this paper with risk of illiquidity implies contagion risk. This adds another dimension to the trade-off between net settlement and RTGS-systems as only net settlement systems are exposed to contagion via the interbank positions, cf. Freixas and Parigi (1998).

The competition between the settlement bank and the RTGS-system in this paper is a competition between two networks. Competition between networks has been analyzed extensively in telecommunications models, cf. Laffont et al. (1998a,b) and Armstrong (1998). A crucial issue is whether the networks are compatible, i.e. whether consumer can belong to different networks and still be able to make phone calls to each other.

[2]Net and gross settlement systems are the two main types of settlement systems. In reality, these co-exist with hybrid systems, which mix characteristics from net settlement and RTGS-systems.

Compatibility is usually not seen within models of LVPS, but indirect settlement makes networks compatible as a bank in network A can submit payments to a bank in network B via a settlement bank. That is, in this paper, compatibility between networks comes at a cost. This idea has been explored for the compatibility of networks handling securities trades, cf. Tapking (2007).

4.2 The model

As mentioned above, there are a RTGS-system and a settlement bank, which competes in the market for settlement services for banks. To ensure that each of these settles payments such that they obtain a positive profit there are two large and two small commercial banks in the economy. The number of payments submitted and received defines the banks' size. Each large bank submits and receives $T+t$ payments; T payments are submitted to (received from) the other large bank and t payments are submitted to (received from) one of the small banks. $T > t > 0$. Correspondingly, each of the small banks submits and receives t payments to one of the large banks and submits (and receives) t to (from) the other small bank, cf. the example in table 4.1. This implies a balanced settlement scheme where each bank receives as many payments as it submits[3].

Table 4.1: Matrix of banks' submitted and received transactions

	Received			
Submitted	Large bank 1	Large bank 2	Small bank 1	Small bank 2
Large bank 1	0	T	0	t
Large bank 2	T	0	t	0
Small bank 1	0	t	0	t
Small bank 2	t	0	t	0

The banks' settlement demand stems from bank customers' transactions, but these transactions are not modelled explicitly. By assumption, the customers are free to deposit their funds in any bank. A deposit insurance bails out the customers in case of bank default. In other words, bank customers' create a demand for settlement of payments but they do not observe how the banks settle these.

[3] The balanced payment scheme simplifies the analysis as it allows us to treat large and small banks symmetrically. An unbalanced payment flow between banks will be discussed below.

Each bank must choose a settlement institution; either the RTGS-system or the settlement bank. This choice is irreversible, e.g. a bank cannot settle payments within the RTGS if it has chosen to settle via the settlement bank. By assumption, banks cannot net out payments bilaterally.

The banks pay for the settlement services offered by the settlement institutions. These costs are covered by charging the fee $p_T > 0$ from the bank customers. p_T is assumed to be constant as we abstract from competition in the market for payment services towards bank customers, i.e. all bank charges p_T no matter the bank size and the choice of settlement institution. If $p_T = 0$ the banks' choice of settlement institutions becomes a problem of cost minimization instead of profit maximization.

The banks' choice of settlement institution is based on their total costs of settlement. The settlement bank charges a fee per transaction, $p_N > 0$, e.g. the total costs of settlement is $(T + t)\, p_N$ for a large bank and $2tp_N$ for a small bank. The total cost of settlement within the RTGS-system consists of a per transaction fee, $p_G > 0$, a fixed price, p_F and of banks' liquidity costs r, e.g. $(T + t)\,(p_G + r) + p_F$ for a large bank and $2t\,(p_G + r) + p_F$ for a small bank. We will discuss the fixed price p_F and the liquidity costs r further below. Note that the RTGS-system's costs of settlement can be due to many different combinations of p_G, p_F and r. The settlement institutions' costs of settlement imply that large banks tend to favor the RTGS-system as their large volume of transactions makes it easier to overcome the fixed price p_F, whereas smaller banks tend to favor the settlement bank as their costs of settlement per transaction are lowest here. This is in line with the results in Holthausen and Rochet (2006).

A central bank owns the RTGS-system. By the end of 2006, more than half of the world's 174 central banks were operating a RTGS-system, cf. Bech et al. (2008). It processes payments continuously on a gross basis. The RTGS-system provides intraday credit to banks as this facilitates immediate processing of payments, cf. Rochet and Tirole (1996). Immediate processing of payments minimizes banks' risks of delayed settlement (liquidity risk) and of settlement of payments below full value when due (credit risk), cf. BIS (2001). Thus, a bank's available amount for payment purposes corresponds to its deposits by the central bank, eventual incoming payments from other banks and its intraday credit. To access intraday credit, banks either pose collateral by depositing assets accepted as collateral by the network owner (Europe) or pay a fee on overdrafts on the bank's account by the network owner (US). In this paper, the RTGS-system provides intraday credit against full collateralization and the liquidity cost is the foregone interest rate $r > 0$ as the banks could have placed the amount held as collateral into an interest-bearing asset instead.

There is a fixed membership fee, $F > 0$, to access the RTGS-system, e.g. the fixed price p_F is chosen to be equal to F. This allows for different interpretations of fixed costs. F can be interpreted as the RTGS-system's costs connected with ongoing development of the system due to technological improvements etc. Another possibility is to interpret F as the banks own costs related to their use of the RTGS-system, i.e. training costs for personnel, equipment etc. Both interpretations imply that the F-term drops out of the profit expressions for the RTGS-system. Large and small banks have the same costs F, but it is easy to extend the model so the banks' membership fee within the RTGS-system depends on banks' size without changing the results. The RTGS-system's marginal price p_G is equal to the fee per transaction and the system has marginal costs per transaction of $c_G > 0$.

The settlement bank is a bank, which is member of the RTGS-system. To simplify the model, the settlement bank has no transactions of its own by assumption. This is natural if the settlement bank is interpreted as a netting system. By assumption, the settlement bank is able and willing to supply settlement services to all banks, which settle indirectly. In reality, a settlement bank might choose to offer settlement services to banks of a certain type, e.g. banks with a large transactions volume to achieve economies of scale just to mention an example.

During a settlement round, the settlement bank nets out as many payments as possible and submits the remaining transactions to the banks in the RTGS-system[4]. Furthermore, the settlement bank receives transactions from banks settling within the RTGS-system to banks settling indirectly, e.g. the settlement bank facilitates payments between members and non-members of the RTGS-system. It is assumed that the settlement bank does not provide intraday credit, i.e. banks are required to deposit funds in the settlement bank corresponding to the amount they will submit indirectly before the settlement round starts. This implies that the settlement bank is less exposed to losses from bank default than the settlement bank in Lai et al. (2006), where the banks settling indirectly pay in the netted amounts of payments after the settlement round has ended. The settlement bank's marginal price p_N is equal to the fee per transaction and its marginal costs per transaction is $c_N > 0$.

[4]In reality, the share of transactions netted out within the settlement bank depends on the settlement banks' liquidity management. Some settlement banks net out as many payments as possible before they submit the remaining ones within the RTGS-system. Others prefer to settle transactions individually on gross basis in the RTGS-system.

The RTGS-system and the settlement bank maximize their profits from settlement services by choosing their marginal prices p_G and p_N. The rest of the variables, T, t, p_T, F, r, c_G and c_N are exogenously given. We will discuss alternatives to profit maximization for the RTGS-system below.

Table 4.2 shows the timing in the model. Eventual defaults of bank(s) and/or the settlement bank are revealed when the game ends at $s = 3$, i.e. it is assumed that payments are not unwound in case of default[5].

Table 4.2: Timing of the game

Time	Action
s=0	Customers deposit
	RTGS-system sets its price p_G
s=1	Settlement bank sets its price p_N
s=2	Banks choose settlement institution
	Banks settling indirectly deposit funds in the settlement bank
s=3	RTGS-system: settlement
	Settlement bank: settlement
s=4	Eventual default of bank(s) and/or settlement bank are revealed
	Settlement bank pays out funds to banks settling indirectly
	Customers withdraw

The RTGS-system and the settlement bank set prices sequentially. The RTGS-system is the first-mover by assumption. The motivation for this assumption is the notion that a bank, which considers acting as a settlement bank, will take the RTGS-system's price and other terms of settlement (banks' liquidity costs from collateralization etc.) into consideration when it decides on offering indirect settlement services to other banks. We will come back to a reversed sequential order in section 4.5. By assumption, the RTGS-system's choice of price is observed perfectly by the settlement bank.

4.3 Solving the model

We solve the model by backwards induction. That is, we start out by considering the banks' choice of settlement institution. Next, we introduce the profits of the settlement

[5]Unwinding of payment means that all payment instructions in a net settlement system are revoked if the system defaults, cf. Shen (1997). Unwinding is irrelevant in RTGS-system as all RTGS-transactions are final as soon as they are processed.

institutions and some restrictions on the prices these institutions can set. Then, the settlement bank sets its price taking the banks' choice of settlement system and the restrictions on the prices into account. Finally, we consider the RTGS-system's price setting. Altogether, this gives us the market solution of the model.

4.3.1 Banks' choice of settlement institution

A bank's choice of the RTGS-system is denoted G (Gross settlement) and its choice of the settlement bank is denoted N (Net settlement). The choice of settlement institution in each case is ordered as the choices by (Large bank 1, Large bank 2, Small bank 1, Small bank 2), i.e. $NGNN$ means that the first large bank chooses the settlement bank, the second large bank chooses the RTGS-system and both small banks choose the settlement bank. There are 16 different combinations of choices between the RTGS-system and the settlement bank with four commercial banks, but only 9 different cases to explore as five of the cases are symmetric, see table 4.3.

The banks' profits depend on the settlement demand, which is $(T + t)$ for large banks and $2t$ for small banks, the banks' price per transaction p_T and the settlement costs within the RTGS-system respectively the settlement bank. As lemma 1 and proposition 1 show, only three of the cases in table 4.3 are candidates for equilibrium.

Lemma 1 *Five of the cases, Case 2: $NGNN$, Case 4: $NNGN$, Case 7: $GGGN$, Case 8: $NGGG$ and Case 9: $NGGN$, are not candidates for equilibrium*

Proof. Comparisons of the profit expressions for the banks in $NGNN$, $NNGN$, $GGGN$, $NGGG$ and $NGGN$ with alternative cases are in the appendix. It turns out that these five cases are equilibria if the following two conditions are fulfilled at the same time

$$\begin{aligned} p_N - p_G &= \frac{F}{T+t} + r \\ p_N - p_G &= \frac{F}{2t} + r \end{aligned}$$

However, these conditions are never fulfilled simultaneously as $T > t$ so $NGNN$, $NNGN$, $GGGN$, $NGGG$ and $NGGN$ are not candidates for equilibrium. ■

The intuition in lemma 1 is that the settlement bank (the RTGS-system) will set an infinitesimally lower price of $p_N - \varepsilon$ ($p_G - \varepsilon$) in Case 2: $NGNN$ and Case 4: $NNGN$

Table 4.3: Profit expressions for the banks in each case

	Case	Large bank, $\pi^j_{L,i}$	Small bank, $\pi^j_{S,i}$
1	GGGG	$\pi^G_{L,i}$=$(T+t)(p_T-p_G-r)-F$	$\pi^G_{S,i}$=$2t(p_T-p_G-r)-F$
2	NGNN,GNNN	$\pi^G_{L,1}$=$(T+t)(p_T-p_G-r)-F$ $\pi^N_{L,2}$=$(T+t)(p_T-p_N)$	$\pi^N_{S,i}$=$2t(p_T-p_N)$
3	GGNN	$\pi^G_{L,i}$=$(T+t)(p_T-p_G-r)-F$	$\pi^N_{S,i}$=$2t(p_T-p_N)$
4	NNGN,NNNG	$\pi^N_{L,i}$=$(T+t)(p_T-p_N)$	$\pi^G_{S,1}$=$2t(p_T-p_G-r)-F$ $\pi^N_{S,2}$=$2t(p_T-p_N)$
5	NNGG	$\pi^N_{L,i}$=$(T+t)(p_T-p_N)$	$\pi^G_{S,i}$=$2t(p_T-p_G-r)-F$
6	NNNN	$\pi^N_{L,i}$=$(T+t)(p_T-p_N)$	$\pi^N_{S,i}$=$2t(p_T-p_N)$
7	GGGN,GGNG	$\pi^G_{L,i}$=$(T+t)(p_T-p_G-r)-F$	$\pi^G_{S,1}$=$2t(p_T-p_G-r)-F$ $\pi^N_{S,2}$=$2t(p_T-p_N)$
8	GNGG,NGGG	$\pi^G_{L,1}$=$(T+t)(p_T-p_G-r)-F$ $\pi^N_{L,2}$=$(T+t)(p_T-p_N)$	$\pi^G_{S,i}$=$2t(p_T-p_G-r)-F$
9	GNNG,NGGN NGNG,GNGN	$\pi^G_{L,1}$=$(T+t)(p_T-p_G-r)-F$ $\pi^N_{L,2}$=$(T+t)(p_T-p_N)$	$\pi^G_{S,1i}$=$2t(p_T-p_G-r)-F$ $\pi^N_{S,2}$=$2t(p_T-p_N)$

Note: $i = 1, 2$ and $j = G, N$. Banks only pay variable fees for submitted payments whereas receiving transactions are free of charge both by the settlement bank and in the RTGS-system. This is without loss of generality as the payment scheme is balanced. Case 2, 4, 7, 8 and 9 are symmetric.

(Case 7: $GGGN$ and Case 8: $NGGG$) in order to attract the remaining demand from the bank, which has chosen the RTGS-system (the settlement bank). Thereby, the equilibrium will change to Case 6: $NNNN$ (Case 1: $GGGG$). In Case 9: $NGGN$ both the settlement bank and the RTGS-system will lower their prices such that large banks choose the RTGS-system and small banks choose the settlement bank, i.e. in this case the equilibrium changes to Case 3: $GGNN$. The following proposition shows that Case 4: $NNGG$ cannot arise in equilibrium.

Proposition 2 *Case 4: NNGG is not a candidate for equilibrium.*

Proof. The two binding price restrictions required if $NNGG$ is a candidate for equilibrium are

$$\begin{aligned} p_N - p_G &\geq \frac{F}{2t} + r \\ p_N - p_G &\leq \frac{F}{T+t} + r \end{aligned}$$

The first restriction ensures that the small banks choose the RTGS-system as their settlement costs within the RTGS-system is smaller than the settlement cost by the settlement bank. The second restriction implies that the large banks prefer indirect settlement as their costs of settlement is lowest by the settlement bank. Both conditions must be fulfilled at the same time if $NNGG$ is an equilibrium. However, this is not the case as $T > t$ so $NNGG$ is not a candidate for equilibrium. ■

Lemma 1 and proposition 1 implies that there are three candidates for equilibrium; *Case 1:* $GGGG$, *Case 3:* $GGNN$ and *Case 6:* $NNNN$. That is, all banks choose to settle either within the RTGS-system or the settlement bank or we end up in a equilibrium where large banks choose the RTGS-system and small banks settle indirectly.

Binding price restrictions in equilibrium

The binding price restrictions in $GGGG$, $GGNN$ and $NNNN$ ensure that neither of the banks will find it optimal to deviate from their choice of settlement institution. The settlement bank and the RTGS-system must take this into account when they set their prices $\{p_N, p_G\}$. In $GGGG$, the binding price restriction is

$$p_N - p_G \geq \frac{F}{2t} + r \tag{4.1}$$

This is derived by comparing the profit for the small and large banks when settling via the RTGS-system resp. the settlement bank. For a small bank, we find the expression in (4.1). The corresponding price restrictions for a large bank is $p_N - p_G \geq \frac{F}{T+t} + r$ but the restriction for the smallest banks is binding since $p_N - p_G \geq \frac{F}{2t} + r \geq \frac{F}{T+t} + r$. As mentioned already, the intuition for this is that large banks can overcome the fixed costs F easier due to their volume of transactions. Therefore, small banks must be compensated for the fixed costs by a low marginal price if it should prefer the RTGS-system. Thus, both large and small banks prefer the RTGS-system instead of the settlement bank if the prices are set in accordance with (4.1), e.g. $GGGG$ is the outcome.

The binding price restriction in $NNNN$ is derived in a similar way. However, the price restriction for the largest banks is now the binding one. Banks with many transactions must face a low marginal price to be willing to settle via the settlement bank, i.e.

$$p_N - p_G \leq \frac{F}{T+t} + r \tag{4.2}$$

There are two binding price restrictions in $GGNN$.

$$\frac{F}{T+t} + r \leq p_N - p_G \leq \frac{F}{2t} + r \tag{4.3}$$

The RTGS-system charges a marginal price, which makes it favourable to the largest banks to settle directly. This explains the lower bound in (4.3). Note that the RTGS-system charges a higher price than in $GGGG$ as there is no need for compensation to the smallest banks. The intuition is the same for the settlement bank. It charges a price that is attractive to the smallest banks only and this explains the upper bound in (4.3). Thus, the cost structures of the settlement institutions imply that they have comparative advantages towards different segments of the market for settlement services. This allows them to charge higher prices than in $NNNN$ or $GGGG$.

4.3.2 Profit expressions for the settlement institutions

The profit expressions for the RTGS-system are

$$\begin{aligned}
\pi_G^{GGGG} &= (2T + 6t)(p_G - c_G) \\
\pi_G^{GGNN} &= 2(T + t)(p_G - c_G) + 2t(p_G - c_G) \\
\pi_G^{NNNN} &= 0
\end{aligned}$$

The profit expressions for the settlement bank are

$$\begin{aligned}
\pi_N^{GGGG} &= 0 \\
\pi_N^{GGNN} &= 4t(p_N - c_N) - 2t(p_G + r) - F \\
\pi_N^{NNNN} &= (2T + 6t)(p_N - c_N)
\end{aligned}$$

For the RTGS-system, these profit expressions depend of the demand for direct settlements and the system's marginal price p_G and marginal cost c_G. It is assumed that $p_G \geq c_G \geq 0$. As we discussed above, the F-term drops out of the RTGS-system's profit as the membership fee covers the costs for ongoing development of the system.

The settlement bank's profit expressions depend on the demand for indirect settlement, its marginal price p_N and its marginal cost c_N. It is assumed that $p_N \geq c_N \geq 0$.

The RTGS-system (settlement bank) serves all demand for settlement services in $GGGG$ ($NNNN$). In $GGNN$ the settlement bank nets out as many payments as possible and settles the remaining payments, t transactions to each of the large banks, within the RTGS-system. This implies costs of $2t\,(p_G + r)$ as the settlement bank pays p_G to the RTGS-system and has opportunity costs of r from the collateralization of payments. The settlement bank pays F to access the RTGS-system. We will show below that the settlement bank charges a higher p_N in $GGNN$ than in $NNNN$ to cover these extra settlement costs. As a consequence, the RTGS-system reaps an additional profit of $2t(p_G - c_G)$ in $GGNN$.

Non-negativity constraints

By assumption, the banks and the settlement institutions will participate in this game if their profits are non-negative. This lays restrictions on p_G and p_N. The lower (upper) bound in the non-negativity constraints ensures a non-negative profit to the settlement institutions (banks).

The non-negativity constraint in $GGGG$ is

$$p_T - r - \frac{F}{T+t} \geq p_G \geq c_G \tag{4.4}$$

The lower bound implies that $\pi_G^{GGGG} \geq 0$. Using the profit expressions for large and small banks in table 4.3, the upper bound comes from solving $\pi_{L,i}^G \geq 0$ and $\pi_{S,i}^G \geq 0$ where the first inequality is binding.

In a similar way, we determine that non-negativity constraint in $NNNN$. That is, we solve $\pi_N^{NNNN} \geq 0$ for the lower bound. The profit expressions for the banks $\pi_{S,i}^N \geq 0$ and $\pi_{L,i}^N \geq 0$ have the same solutions and this explains the upper bound. That is, the non-negativity constraint in $NNNN$ is

$$p_T \geq p_N \geq c_N \tag{4.5}$$

The non-negativity constraints in $GGNN$ ensure non-negative profits for the largest banks and the RTGS-system respectively non-negative profits for the smallest banks and the settlement bank, i.e.

$$p_T - r - \frac{F}{T+t} \geq p_G \geq c_G \tag{4.6}$$

$$p_T \geq p_N \geq c_N + \frac{(p_G + r)}{2} + \frac{F}{4t} \tag{4.7}$$

The upper limits in these expressions follow from solving $\pi^G_{L,i} \geq 0$ for the large banks and $\pi^N_{S,i} \geq 0$ for the small banks by use of the relevant profit expressions from table 4.3. The lower bounds follow from solving $\pi^{GGNN}_G \geq 0$ for the RTGS-system and $\pi^{GGNN}_N \geq 0$ for the settlement bank.

4.3.3 Market equilibrium

We have now found the cases that are candidates for equilibrium and the restrictions on the price setting by the settlement institutions. We now turn to these price choices.

The settlement bank's choice of p_N

In $GGGG$, the settlement bank sets its most aggressive price to try to attract demand using (4.5), i.e.

$$p_N = c_N \tag{4.8}$$

In $GGNN$, the settlement bank only serves the small banks, i.e. p_N is set in accordance with (4.3) such that

$$\begin{aligned} p_N &= p_G + \frac{F}{2t} + r \\ \pi^{GGNN}_N &= 2t(p_G + r) + F - 4tc_N \end{aligned} \tag{4.9}$$

In $NNNN$, the settlement bank sets p_N using (4.2) such that

$$p_N = p_G + \frac{F}{T+t} + r \tag{4.10}$$

$$\pi^{NNNN}_N = (2T + 6t)(p_G + \frac{F}{T+t} + r - c_N) \tag{4.11}$$

As discussed above, it is relatively easy to check that the settlement bank sets a lower price in $NNNN$ than in $GGNN$.

A comparison of the settlement bank's profit in $GGGG$, $GGNN$ and $NNNN$ gives

$$\begin{aligned}
\pi_N^{GGNN} &\geq \pi_N^{GGGG} \Leftrightarrow p_G \geq 2c_N - \frac{F}{2t} - r \\
\pi_N^{NNNN} &\geq \pi_N^{GGGG} \Leftrightarrow p_G \geq c_N - \frac{F}{T+t} - r \qquad (4.12) \\
\pi_N^{NNNN} &\geq \pi_N^{GGNN} \Leftrightarrow p_G \geq \frac{T+t}{T+2t} c_N - \frac{(T+5t)\,F}{2(T+t)(T+2t)} - r \qquad (4.13)
\end{aligned}$$

The settlement bank's profit expressions imply that for some parameter values, the settlement bank always obtains a higher profit in $NNNN$ than in $GGNN$. There are either three, $GGGG$, $GGNN$ and $NNNN$, or two, $GGGG$ and $NNNN$, candidates for equilibrium. Lemma 2 and 3 prove this formally. Figure 4.1a (4.2a) illustrates the settlement bank's profit function when there are three (two) candidates for equilibrium. We focus on the situation with three candidates for equilibrium here and come back to the situation with two candidates later.

Lemma 3 *The slope of π_N^{NNNN} is larger than the slope of π_N^{GGNN}*

Proof. This follows from the settlement bank's profit expressions as $(2T+6t)\,p_N \geq 4tp_N$ ■

Lemma 4 *The intercepts at which π_N^{GGNN} cross the profit axis is larger than for π_N^{NNNN} when the marginal cost of the settlement bank is high enough.*

Proof. Comparing the intercepts with the profit-axis in figure 4.1 for π_N^{GGNN} and π_N^{NNNN} gives

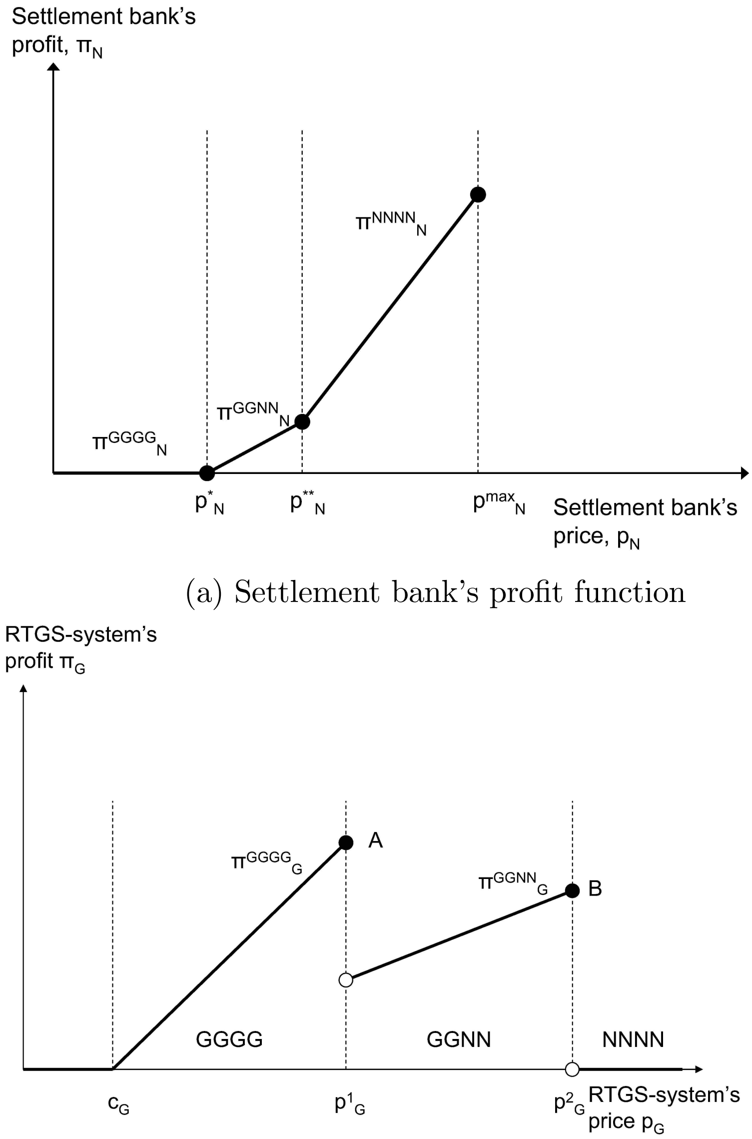
$$\begin{aligned}
-4tc_N - 2t(p_G + r) - F &\geq -(2T+6t)\,c_N \Leftrightarrow \qquad (4.14) \\
\frac{t}{T+t}(p_G + r) + \frac{F}{2T+2t} &\leq c_N
\end{aligned}$$

■

We will show below that (4.14) holds if

$$c_N \geq \frac{T\,(T+2t) - 3t^2}{2\,(T+t)^3} F \qquad (4.15)$$

Figure 4.1: Profit functions with three candidates for equilibrium



(a) Settlement bank's profit function

(b) RTGS-system's profit function

Note: The candidates for equilibrium are $GGGG$, $GGNN$ and $NNNN$. The location of point A and B in panel b depends on (4.17). p_N^{max} is given by (4.10).

The RTGS-system's choice of p_G

When at least one of the non-negativity constraints (4.4)-(4.6) are fulfilled, the RTGS-system always obtain a higher profit in either $GGGG$ or $GGNN$ than in $NNNN$. The RTGS-system's profit function, shown in figure 4.1b, follows from lemma 4.

Lemma 5 $\pi_G^{GGGG} \geq \pi_G^{GGNN}$

Proof. This follows from the profit expressions for the RTGS-system in $GGGG$ and $GGNN$ since $2T + 6t > 2T + 4t$ ■

The RTGS-system set the price p_G^1 in $GGGG$. This is the highest possible price the RTGS-system can charge before the small banks choose to settle indirectly given the reaction of the settlement bank, i.e. from (4.1)

$$p_G^1 = c_N - r - \frac{F}{2t}$$

However, to ensure that all banks and settlement institutions are willing to participate in the game, p_G^1 must fulfill (4.4).

The RTGS-system sets p_G^2 in $GGNN$ such that only large banks settle within the RTGS-system. The settlement bank is only willing to accept $GGNN$ as equilibrium if it obtains the same profit as in $NNNN$, i.e. p_G^2 must fulfill

$$\pi_N^{GGNN}(p_G^2) = \pi_N^{NNNN}(p_G^2) \tag{4.16}$$

so p_G^2 is given by (4.13). The profit for the RTGS-system must be non-negative if $GGNN$ is to be equilibrium, i.e. p_G^2 must fulfill (4.6).

The choice between $GGGG$ and $GGNN$ as the market equilibrium for the RTGS-system implies a trade-off. The RTGS-system can either charge a low price to attract all demand in $GGGG$ or charge a higher price an serve demand from the large banks only in $GGNN$. The RTGS-system chooses the most profitable market equilibrium, e.g. $GGGG$ is the market equilibrium if

$$\pi_G^{GGGG}(p_G^1) \geq \pi_G^{GGNN}(p_G^2) \Leftrightarrow c_N \geq \frac{c_G + r}{2} + \frac{T(T+3t) - 2t^2}{4t^2(T+t)}F \tag{4.17}$$

Lemma 6 *When the non-negativity constraints in (4.4)-(4.6) are fulfilled and (4.17) is fulfilled, $GGGG$ is the equilibrium. The equilibrium prices are* $\{p_N^1, p_G^1\} = \{c_N, c_N - r - \frac{F}{2t}\}$

Lemma 7 *When the non-negativity constraints in (4.4)-(4.6) are fulfilled and (4.17) is violated, GGNN is the equilibrium. The equilibrium prices are*

$$\begin{aligned} p_N^2 &= \frac{T+t}{T+2t}c_N + \frac{T(T+2t)-3t^2}{(T+t)(T+2t)}\frac{F}{2t} \\ p_G^2 &= \frac{T+t}{T+2t}c_N - \frac{T+5t}{2(T+t)(T+2t)}F - r \end{aligned}$$

Lemma 8 *$NNNN$ is the equilibrium when the non-negativity constraints for the RTGS-system (4.4)-(4.6) are violated, but the non-negativity constraint for the settlement bank (4.5) is fulfilled. The equilibrium prices are* $\{p_N, p_G\} = \left\{c_G + \frac{F}{T+t} + r, c_G\right\}$

(4.15) can now be derived by inserting $p_G = p_G^2$ in (4.14) since this is the price at which π_N^{GGNN} and π_N^{NNNN} intersect.

4.3.4 Market solution with two candidates for equilibrium

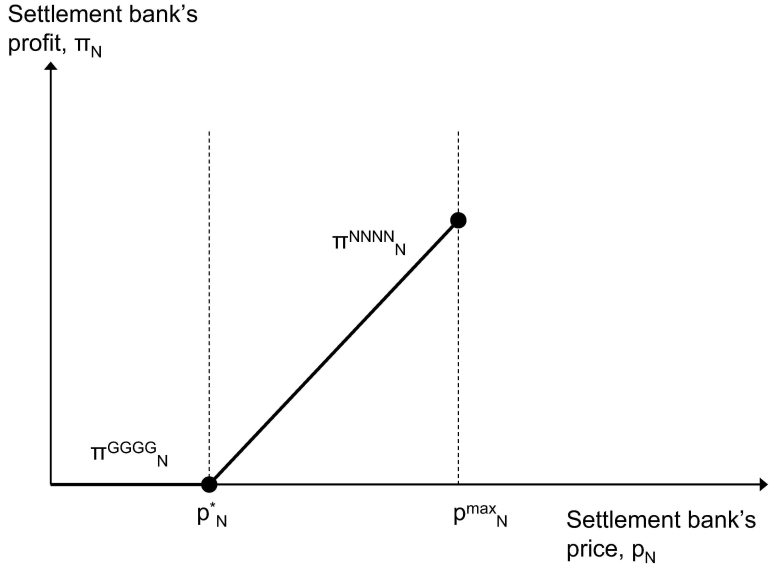
To complete the analysis of the model we must consider the situation with two candidates for equilibrium, $GGGG$ and $NNNN$. The profit functions for the settlement bank and the RTGS-system in this situation are shown in figure 4.2. Here, (4.15) is not fulfilled such that the settlement bank reaps the highest profit from serving all demand for settlement services for all values of p_N, e.g. $\pi_N^{NNNN} \geq \pi_N^{GGNN}$.

The RTGS-system must set p_G such that the settlement bank gets the same profit in $GGGG$ and $NNNN$, e.g. p_G is given by (4.12).

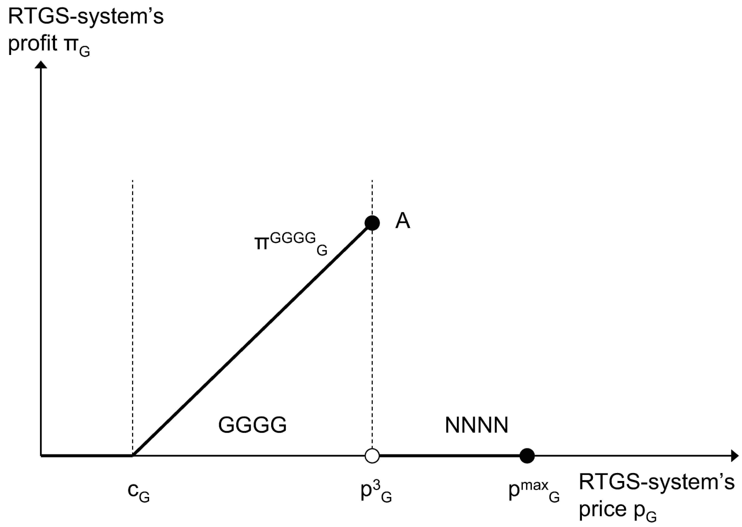
Lemma 9 *When GGGG and NNNN are candidates for equilibrium and if (4.4) and (4.5) are fulfilled, GGGG is the market equilibrium with equilibrium prices* $\{p_N, p_G\} = \left\{c_N, c_N - \frac{F}{T+t} - r\right\}$ *which follows from (4.8) and (4.12).*

Lemma 10 *When GGGG and NNNN are candidates for equilibrium and if (4.4) is violated and (4.5) is fulfilled, NNNN is the market equilibrium with equilibrium prices* $\{p_N, p_G\} = \left\{c_G + \frac{F}{T+t} + r, c_G\right\}$ *using the lower bound in (4.4) and (4.10).*

Figure 4.2: Profit functions with two candidates for equilibrium



(a) Settlement bank's profit function



(b) RTGS-system's profit function

Note: $GGGG$ and $NNNN$ are the only candidates for equilibrium. p_N^{max} and p_G^{max} are given by (4.10) and (4.12).

4.4 Welfare

To evaluate the efficiency of the market solution, we consider the social planner's solution. The social planner maximizes the total welfare, which is equal to the settlement institutions' profit plus the banks' profit, i.e.

$$\begin{aligned}
W^{GGGG} &= (2T+6t)(p_T - c_G - r) - 4F \\
W^{GGNN} &= (2T+2t)(p_T - c_G - r) - 3F + 4t(p_T - c_N) - 2t(c_G + r) \\
W^{NNNN} &= (2T+6t)(p_T - c_N)
\end{aligned}$$

p_G and p_N drop out of the welfare expressions as the social planner only takes the costs of settlement and the banks' price towards their customers, p_T, into consideration. A comparison of the welfare expressions gives

$$W^{GGGG} \geq W^{GGNN} \Leftrightarrow c_N \geq \frac{c_G + r}{2} + \frac{F}{4t} \tag{4.18}$$

$$W^{GGNN} \leq W^{NNNN} \Leftrightarrow c_N \leq \frac{T+2t}{T+t}\left(c_G + r\right) + \frac{3F}{2\left(T+t\right)} \tag{4.19}$$

$$W^{GGGG} \leq W^{NNNN} \Leftrightarrow c_N \leq c_G + r + \frac{2F}{T+3t} \tag{4.20}$$

One can show that the right hand sides (RHS) of these inequalities fulfil

$$\begin{aligned}
RHS(4.18) &\geq RHS(4.20) \geq RHS(4.19) \qquad (4.21)\\
\text{when } c_G + r &\leq \frac{T-5t}{2t\left(T+3t\right)} F
\end{aligned}$$

and vice versa when $c_G + r \geq \frac{T-5t}{2t(T+3t)} F$.

4.4.1 Inefficient market solution

The market solution is inefficient in the sense that it differs from the social planner's solution when $F > 0$. To see this, recall that the RTGS-system's profit expressions determines the market equilibrium, e.g. by comparison of these profit expressions we find

$$\pi_G^{GGNN} \leq \pi_G^{NNNN} \Leftrightarrow c_N \leq \frac{T+2t}{T+t}(c_G+r) + \frac{T+5t}{2(T+t)^2}F \tag{4.22}$$

$$\pi_G^{GGGG} \leq \pi_G^{NNNN} \Leftrightarrow c_N \leq c_G + r + \frac{F}{2t} \tag{4.23}$$

Furthermore, $\pi_G^{GGGG} \geq \pi_G^{GGNN}$ is given by (4.17). One can show that

$$\begin{aligned} RHS(4.17) &\geq RHS(4.23) \geq RHS(4.22) \\ \text{when } c_G + r &\leq \frac{T(T+t) - 4t^2}{2t^2(T+t)}F \end{aligned} \tag{4.24}$$

and vice versa for $c_G + r \geq \frac{T(T+t)-4t^2}{2t^2(T+t)}F$. Thus, the difference between the market solution and the welfare optimal solution depends (4.21) and (4.24). Since $\frac{T(T+t)-4t^2}{2t^2(T+t)}F > \frac{T-5t}{2t(T+3t)}F$ there are three possibilities:

1. $\frac{T(T+t)-4t^2}{2t^2(T+t)}F \leq c_G + r$. The market solution is inefficient in region A (B) as the market equilibrium is $GGNN$ ($GGGG$) but $NNNN$ is welfare optimal here, see figure 4.3a.

2. $\frac{T-5t}{2t(T+3t)}F \geq c_G + r$. The market solution is inefficient in region C (D, E) where $GGNN$ ($NNNN$, $NNNN$) is the market solution, but $GGGG$ ($GGGG$, $GGNN$) is optimal from the social planner's point of view. Figure 4.3b illustrates this case.

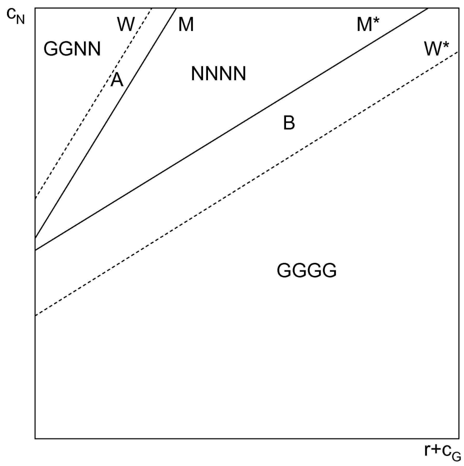
3. $\frac{T(T+t)-4t^2}{2t^2(T+t)}F > c_G + r > \frac{T-5t}{2t(T+3t)}F$. The market solution is inefficient except for one region, see figure 4.3c. The market solution in region F (G, H) is $GGNN$ ($NNNN$, $NNNN$) when $GGGG$ ($GGGG$, $GGNN$) is welfare optimal. $NNNN$ is welfare optimal in region I, J, and K, but $GGGG$ is the market solution here.

The third possibility arises when the large banks are much larger than the small banks, i.e. $T(T+t) > 4t^2$. The high degree of inefficiency arises because the market solution is completely opposite of the social planner's solution except for one region. In the other two cases, the large banks are not that much larger than the small banks and the market solution is closer to the social planner's solution. Thus, the inefficiency of the market solution is smaller in these cases.

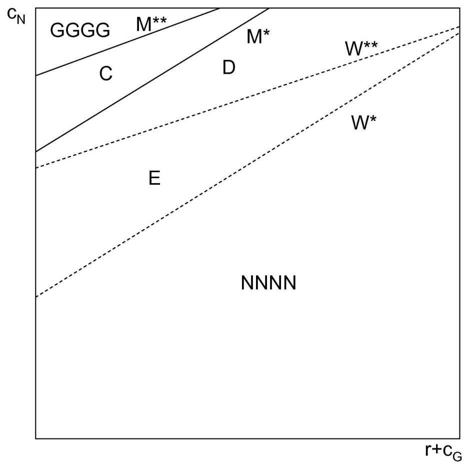
Proposition 2 proves the inefficiency of the market solution.

Proposition 11 *The market solution is inefficient in the sense that it differs from the welfare optimal solution*

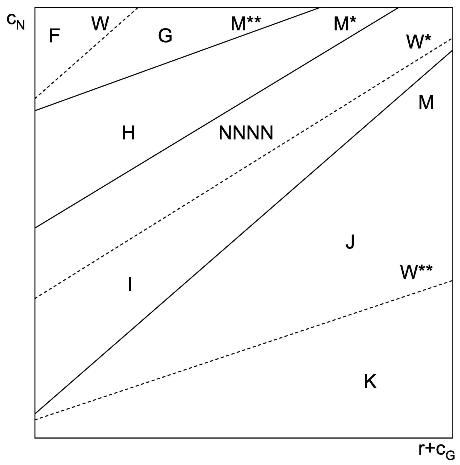
Figure 4.3: Inefficient market solution



(a) $\frac{T(T+t)-4t^2}{2t^2(T+t)}F \leq c_G + r$



(b) $\frac{T-5t}{2t(T+3t)}F \geq c_G + r$



(c) $\frac{T(T+t)-4t^2}{2t^2(T+t)}F > c_G + r > \frac{T-5t}{2t(T+3t)}F$

Note: W, W* and W** corresponds to (4.19), (4.20) and (4.18). M, M* and M** corresponds to (4.22), (4.23) and (4.17). The market solution is inefficient in the regions marked $A, B, ..., K$.

Proof. The inefficiency of the market solution when $\frac{T(T+t)-4t^2}{2t^2(T+t)}F \leq c_G + r$ follows from (4.21), (4.24) and the fact that

$$RHS(4.17) > RHS(4.18) \quad (4.25)$$
$$RHS(4.19) > RHS(4.22) \quad (4.26)$$
$$RHS(4.20) < RHS(4.23) \quad (4.27)$$

(4.26)-(4.27) are fairly easy to show and holds when $F > 0$ and $T > t > 0$.
The inefficiency of the market solution when $\frac{T-5t}{2t(T+3t)}F \geq c_G + r$ follows from (4.21), (4.24), (4.25)-(4.27) and from $RHS(4.23) \geq RHS(4.18)$. One can show that the latter inequality holds when $\frac{T-5t}{2t(T+3t)}F \geq c_G + r$.
When $\frac{T(T+t)-4t^2}{2t^2(T+t)}F \geq c_G + r \geq \frac{T-5t}{2t(T+3t)}F$, the inefficient market solution follows from (4.21), (4.24), (4.25)-(4.27) and from the fact that $RHS(4.23) \geq RHS(4.17), RHS(4.20) \geq RHS(4.22)$ and $RHS(4.22) \geq RHS(4.18)$ when $c_G + r$ is in the interval. ■

Proposition 2 also applies to the case where $GGGG$ and $NNNN$ are the only candidates for equilibrium. However, in this case, the inefficiency of the market solution arises from the outset as $GGNN$ cannot occur as market equilibrium.

4.4.2 Discussion of welfare results

One explanation for the inefficient market solution is the different cost structures of the RTGS-system and the settlement bank. This implies that the settlement institutions have different comparative advantages towards banks of different size, e.g. the different cost structures works as a kind of product differentiation.

The comparative advantages for the RTGS-system and the settlement bank vanishes when banks are symmetric such that $T = t$ or without membership fees in the RTGS-system. Then, the settlement systems supply a homogeneous good, settlement of payments, as the following proposition shows.

Proposition 12 *With three candidates for equilibrium, the market solution is efficient when the banks are of equal size, $T = t$, or without membership fees in the RTGS-system, $F = 0$.*

Proof. The only relevant parameter range to consider when $T = t$ or $F = 0$ is $\frac{T(T+t)-4t^2}{2t^2(T+t)}F \leq c_G + r$ since $c_G + r \geq 0$ by assumption. (4.25)-(4.27) are then fulfilled with equality such that the market solution and the social planner's solution become equal. That is, the market solution becomes efficient. ■

Note that proposition 3 does not apply to the case where $GGGG$ and $NNNN$ are the only candidates for market equilibrium, e.g. the inefficiency remains here even though $T = t$ or $F = 0$ as $GGNN$ is welfare optimal for some parameter values.

Proposition 3 implies that the settlement institutions price at marginal costs just like the social planner does, e.g. the prices are set equal to the lower bounds in (4.4)-(4.5) whereby the RTGS-system and the settlement bank obtain zero profit. The banks are indifferent between the RTGS-system and the settlement bank as the settlement costs are the same ($p_N = p_G + r + \frac{F}{2t}$ when $T = t$ and $p_N = p_G + r$ when $F = 0$) in all 9 possible cases, see table 4.3.

Proposition 3 is in line with the logic from the Bertrand model. In a standard Bertrand model with two firms, homogeneous goods and simultaneous price setting and where firms have the same marginal (and no fixed) costs both firms in a duopoly price at the marginal cost and neither of the firms make profits. Thus, the inefficient market solution we found above stems from product differentiation due to different cost structures of the settlement institutions. The product differentiation allows the RTGS-system and the settlement bank to price above or equal to marginal costs depending on how many banks they serve with settlement services.

Another explanation for the inefficient market solution is the inelastic demand for settlement services by banks, i.e. the banks' demand for settlement services is the same no matter the prices set by the settlement institutions. Further, the banks in this model choose one settlement institution only, whereas agents in other models can demand goods from more than one producer. Both the inelastic demand and the irreversible choice of settlement institution tend to give the RTGS-system and the settlement bank market power on a sub-set of the market or the whole market for settlement services. This weakens the price competition between the suppliers of settlement services.

The sequential price setting with the RTGS-system and the assumption of a profit-maximizing RTGS-system are other aspects of the market inefficiency. The latter aspect is discussed next. We come back to the market solution under simultaneous price setting respectively sequential price setting with the settlement bank as first-mover in section 4.5.

4.4.3 Can the RTGS-system limit the market inefficiency?

The market solution is inefficient when both settlement institutions maximize profits. This section analyzes whether a publicly owned RTGS-system can limit the market inefficiency by different pricing strategies. The settlement bank is still profit-maximizing and the sequential order of the game is the same.

Cost-covering RTGS-system

The first pricing strategy to consider is to let the RTGS-system price at its marginal cost, i.e. $p_G = c_G$. Some central banks prefer a cost-covering RTGS-system rather than making profits on settlement services in a RTGS-system.

A cost-covering RTGS-system cannot change its prices in $NNNN$ and $GGNN$. It has already set the cost-covering price $p_G = c_G$ in $NNNN$ and the RTGS-system's price in $GGNN$ is unchangeable as this is set such that the settlement bank is indifferent between $NNNN$ and $GGNN$, see (4.16). But the RTGS-system can change its price in $GGGG$ such that (4.17) changes to

$$\begin{aligned} \pi_G^{GGGG}(c_G) &\leq \pi_G^{GGNN}\left(p_G^2\right) \Leftrightarrow \\ c_N &\geq \frac{T+2t}{T+t}(c_G+r)+\frac{T+5t}{2(T+t)^2}F \end{aligned}$$

which is equal to (4.22). This implies that (4.24) is fulfilled with equality, e.g. only the situation illustrated in figure 4.3a is relevant here when evaluating the implications for inefficiency of the market solution. Furthermore, (4.20) and (4.23) become equal as both the RTGS-system and the social planner prices at marginal costs in $GGGG$ and $NNNN$, e.g. the market solution becomes efficient in region B in figure 4.3a. But the RTGS-system charges $p_G \geq c_G$ in $GGNN$, see (4.6), such that the inefficiency in region A in figure 4.3a remains.

Thus, the market solution is still inefficient with a cost-covering RTGS-system, but to a lesser extent than with a profit-maximizing RTGS-system.

Welfare-maximizing RTGS-system

An efficient market solution can be achieved if the RTGS-system maximizes welfare. Two different strategies are needed; 1) different price setting by the RTGS-system in $GGGG$, 2) subsidies.

Efficiency can be achieved in region C, D, F, G, I, J and K by a different price setting by the RTGS-system in $GGGG$. As before, the RTGS-system's price in $GGNN$ and $NNNN$ are unchangeable.

In region C and F the pricing in $GGGG$ must be changed such that the market solution changes from $GGNN$ to $GGGG$. Thus, the RTGS-system's price in $GGGG$ is changed to $p_G = \widehat{p_G}$ such that (4.17) and (4.18) are equal, i.e.

$$\begin{aligned} \pi_G^{GGGG}\left(\widehat{p_G}\right) &\leq \pi_G^{GGNN}\left(p_G^2\right) \Leftrightarrow \\ c_N &\geq \frac{(T+2t)\,r + (T+3t)\,\widehat{p_G} - tc_G}{T+t} + \frac{(T+5t)\,F}{2(T+t)} \end{aligned} \tag{4.28}$$

The right hand sides of (4.18) and (4.28) are equal when

$$\widehat{p_G} = \frac{c_G - r}{2} + \frac{T + t - 2t\,(T+5t)}{4t\,(T+3t)}F$$

In region D, G, I, J and K the price setting in $GGGG$ must be changed such that the market solution changes from $NNNN$ to $GGGG$. The RTGS-system's price in $NNNN$ equals marginal costs so changing the price setting in $GGGG$ implies that $p_G = \widetilde{p_G} = c_G$ since (4.20) and (4.23) are equalized by $\widetilde{p_G}$. Thus, in contrast to the cost-covering RTGS-system, a changed pricing by a welfare-maximizing RTGS-system can overcome the inefficiency from the unchangeable price in $GGNN$.

A subsidy makes the market solution efficient in region A, B, E and H in figure 4.3a-4.3c. A subsidized RTGS-system implies that $p_G < c_G$ such that the settlement bank obtains a negative profit, e.g. in region E and H where $GGNN$ is welfare optimal, but $NNNN$ is the market equilibrium the subsidy must fulfill

$$\pi_N^{NNNN} < 0 \Leftrightarrow p_G < c_N - \frac{F}{T+t} - r \tag{4.29}$$

$$\pi_N^{GGNN} > 0 \Leftrightarrow p_G \geq 2c_N - \frac{F}{t} - r \tag{4.30}$$

using (4.9) and (4.11). One can show that (4.29) and (4.30) are fulfilled at the same time when

$$c_N < \frac{T}{t\,(T+t)}F$$

In region A (B), where market equilibrium is $GGNN$ ($GGGG$) and $NNNN$ is welfare optimal, the subsidy must be set such that $\pi_N^{NNNN} > 0$ and $\pi_N^{GGNN} < 0$.

That is, a welfare-maximizing RTGS-system can achieve an efficient market solution by a changed price-setting for the RTGS-system and by subsidies. Subsidization is a costly policy tool as it is financed via taxes but this is realistic if the welfare-maximizing RTGS-system is thought of as a public good for the financial sector.

4.5 Robustness of results

In this section we discuss the assumption of a balanced payment flow. Moreover, we consider the consequences of reversed sequential order and of simultaneous price setting by the settlement institutions.

4.5.1 Unbalanced payment flow between banks

As a starting point, note that a more detailed, but still balanced, payment flow than the one in the basic model, does not change the results, as the banks' profit expressions are unchanged. To mention an example, the total transactions submitted and received by a small bank is still equal to $2t$ if the small bank submits $\frac{t}{2}$ to each of the large banks and t to the other small bank and receives t from each of the large banks.

Thus, the assumption of a balanced payment scheme between banks is crucial for the results as this allows us to treat banks symmetrically. An unbalanced payment scheme changes the profit expressions for the banks and settlement institutions because it is assumed that only the submitting bank is charged for a transaction[6]. To see this consider a large bank settling directly and let the RTGS-system charge $\frac{9}{10}$ of the total fee per transaction on submitted payments and $\frac{1}{10}$ on received payments. With a balanced payment scheme, the profit for the large bank becomes

$$\left(\frac{9}{10}\left(T+t\right)+\frac{1}{10}\left(T+t\right)\right)\left(p_T - p_G - r\right) - F = \left(T+t\right)\left(p_T - p_G - r\right) - F$$

[6] Only charging the submitter of a payment makes the model fairly simple to analyze. The assumption is realistic as many network owners charge a flat fee per transaction, cf. BIS (2005). Moreover, this assumption is in line with the two-sided markets theory, where either (or both) side(s) of the market pays for a transaction provided by a platform. Gans and King (2003) shows the neutrality of the interchange fee charged for a transaction from the card issuer to the acquirer's platform on the credit cards market. It implies that either (or both) side(s) of the market can pay the interchange fee. This result hinges upon the assumption that a change in one of the prices of settlement is accompanied by a change in all other prices such that the total profit of settlement is unchanged for a bank. If p_N increases with α, p_T must also increase by α to keep the profit of indirect settlement unchanged as $(p_T + \alpha) - (p_N + \alpha) = (p_T - p_N)$.

This profit is equal to the large bank's profit if fees are only charged on either submitted or received payments, cf. table 4.3. If the payment scheme is unbalanced, we let the large bank submit $T+t$ payments and receive $T+\frac{3}{2}t$. The large bank's profit is then

$$\left(\frac{9\,(T+t)}{10}+\frac{T+\frac{3}{2}t}{10}\right)(p_T-p_G-r)-F=\left(T+\frac{21}{20}t\right)(p_T-p_G-r)-F$$

That is, an unbalanced payment scheme alters the equilibrium prices, but the intuition from the basic model is the same. Thus, the banks have balanced payment scheme to keep the model as simple as possible.

4.5.2 Reversed sequential order

The settlement bank is the first-mover when the sequential order, in which the prices $\{p_N, p_G\}$ is set, is reversed. The RTGS-system will take p_N into account when determining p_G and finally, the banks choose a settlement institution. In line with the results when the RTGS-system is the first-mover, the settlement bank tends to prefer $GGNN$ or $NNNN$ as the market equilibrium as it obtains a positive profit in these cases.

When $GGGG$ and $NNNN$ are the only candidates for equilibrium, the settlement bank will set the same equilibrium prices as in lemma 8 and 9. p_N and p_G are set in accordance with the binding price restrictions in (4.1)-(4.2) and the settlement bank (RTGS-system) will set its lowest possible price using (4.4) [(4.5)] in $GGGG$ ($NNNN$) to attract demand.

The same arguments imply that the equilibrium prices are unchanged in $GGGG$ and $NNNN$ when $GGGG$, $GGNN$ and $NNNN$ are candidates for equilibrium, cf. lemma 5 and 7. But the price setting in $GGNN$ changes as RTGS-system will only accept $GGNN$ as the equilibrium if $\pi_G^{GGGG}=\pi_G^{GGNN}$. One can show that this requires $\{p_N,p_G\}=\left\{c_G+r+\frac{F}{2t},c_G\right\}$. A comparison of the settlement bank's profits gives

$$\begin{aligned}
\pi_N^{NNNN} &\geq \pi_N^{GGNN}\Leftrightarrow c_N\leq\frac{T+2t}{T+t}(c_G+r)+\frac{T+5t}{2\,(T+t)^2}F && (4.31)\\
\pi_N^{GGNN} &\geq \pi_N^{GGGG}\Leftrightarrow c_N\leq\frac{c_G+r}{2}+\frac{F}{4t} && (4.32)\\
\pi_N^{NNNN} &\geq \pi_N^{GGGG}\Leftrightarrow c_N\leq c_G+r+\frac{F}{T+t} && (4.33)
\end{aligned}$$

Even though the inequalities in (4.32) and (4.18) are the same, the market solution in inefficient as (4.31) and (4.33) differ from (4.19)-(4.20). This is in line with proposition 2 and this result also applies to the case where $GGGG$ and $NNNN$ are the only candidates for market equilibrium, i.e. $GGNN$ is not market equilibrium although this can be welfare optimal.

4.5.3 Simultaneous price setting

With simultaneous price setting, $GGGG$ and $NNNN$ are the only candidates for equilibrium.

Lemma 13 *GGNN is not a candidate for equilibrium under simultaneous price setting*

Proof. If $GGNN$ is an equilibrium, the RTGS-system and the settlement bank must choose p_G and p_N such that both the large and small banks are indifferent between the settlement institutions. If this is not the case, either of the settlement institutions will attract all banks whereby the equilibrium changes to $GGGG$ or $NNNN$. The banks are indifferent between the RTGS-system and the settlement bank when the binding price restrictions in (4.3) are fulfilled with equality, i.e.

$$\frac{F}{T+t} + r = p_N - p_G = \frac{F}{2t} + r$$

However, this is not possible as $T > t$ so $GGNN$ cannot be an equilibrium in pure strategies under simultaneous price setting. ∎

This result implies that both settlement institutions have incentives to lower the price in order to attract all demand for settlement services, e.g. $GGGG$ or $NNNN$ is the equilibrium. Note also that the market solution becomes inefficient when GGNN cannot arise as market equilibrium as we discussed in section 4.4.1.

As above, the RTGS-system will set its most aggressive price when the settlement bank serves all demand, i.e. $p_G^{S1} = c_G$. The settlement bank's price is determined by (4.2) so the equilibrium prices in $NNNN$ become $\left\{p_N^{S1}, p_G^{S1}\right\} = \left\{c_G + \frac{F}{T+t} + r, c_G\right\}$, e.g. the equilibrium prices in NNNN are the same under sequential price setting with the RTGS-system as the first-mover. The settlement bank must obtain a non-negative profit if $NNNN$ is an equilibrium, i.e. p_N^{S1} must fulfill (4.5).

When all banks choose the RTGS-system, the settlement bank will set its most aggressive price, e.g. p_N^{S2} is equal to the lower bound in (4.7) and the RTGS-system's price in accordance with (4.1). This implies that the equilibrium prices in $GGGG$ change

to
$\left\{p_N^{S2}, p_G^{S2}\right\} = \left\{c_N + \frac{(p_G+r)}{2} + \frac{F}{4t}, 2c_N - \frac{F}{2t} - r\right\} = \left\{2c_N, 2c_N - \frac{F}{2t} - r\right\}$. $GGGG$ is an equilibrium if p_G^{S2} fulfils (4.4).

The following lemma implies that there is no market solution in pure strategies when $\frac{c_G+r}{2} + \frac{F}{2(T+t)} < c_N < \frac{c_G+r}{2} + \frac{F}{4t}$.

Lemma 14 *If the difference in the settlement institutions' marginal prices are large (small) enough all banks choose $GGGG$ ($NNNN$).*

Proof. According to (4.1) all banks will choose $GGGG$ if the smallest banks find it optimal to do so, i.e. if

$$\begin{aligned}
\pi_{S,i}^G(p_G^{S2}, p_N^{S2}) &\geq \pi_{S,i}^N(p_G^{S1}, p_N^{S1}) \Leftrightarrow \\
2t\left(p_G^{S2} + r\right) + F &\leq 2tp_N^{S1} \Leftrightarrow \\
c_N &\leq \frac{c_G + r}{2} + \frac{F}{2\left(T+t\right)}
\end{aligned}$$

According to (4.2) all banks will choose $NNNN$ if the largest bank find it optimal to do so, i.e. if

$$\begin{aligned}
\pi_{L,i}^G(p_G^{S2}, p_N^{S2}) &\leq \pi_{L,i}^N(p_G^{S1}, p_N^{S1}) \Leftrightarrow \\
(T+t)\left(p_G^{S2} + r\right) + F &\geq (T+t)\, p_N^{S1} \Leftrightarrow \\
c_N &\geq \frac{c_G + r}{2} + \frac{F}{4t}
\end{aligned}$$

■

4.6 Risk of illiquidity

The consequences of an illiquid (or default) settlement bank can be widespread. Thus, the monetary authorities tend to rescue settlement banks in distress and the Federal Reserve Bank's bailout of Bear Sterns and the acceptance of a lower quality of collateral during the current financial crisis are examples of this, cf. Jaffee and Perlow (2008) and Federal Reserve (2008). In this section, we extend the model by allowing the settlement bank and the banks to become illiquid with probability η respectively β, $\eta, \beta \in [0, 1]$.

A (settlement) bank "defaults" when it is solvent but illiquid such that it cannot settle payments. We use the term default to describe this situation in the following and in the appendix). The counterparties of a default bank will also default if the payments submitted by the default bank are uncollateralized. That is, three different situations can arise in case of bank default:

1. A bank settling directly within the RTGS-system defaults. Collateral is transferred from the default bank to its counterparties.

2. The settlement bank defaults. All banks settling indirectly default as they become illiquid and banks settling directly within the RTGS-system default because the settlement bank cannot pose collateral for payments submitted in this system.

3. A bank settling indirectly defaults. This makes the settlement bank illiquid with the same consequences as in the previous case.

The latter two cases imply contagious effects as a default spreads from one bank to another. This highlights the counterparty risk involved in indirect settlement. Banks settling within the RTGS-system are protected against contagion as long as the settlement bank does not default. Thus, contagion effects add to the costs of settlement and the banks' size when the banks make their choice of settlement channel.

The extension of the model implies that new types of equilibria can arise. There are now four scenarios to consider based on the settlement bank's profit function but two of these have the same outcome. In the first case, $GGGG$, $GGNN$ and $NNNN$ are candidates for equilibrium, whereas $GGGG$ and $NNNN$ are possible in market equilibrium in the second scenario. This corresponds to the market solution of the model without risk. The risk of default is high in the third case where $GGGG$ and $GGNN$ are the only candidates for equilibrium. This reflects that the settlement bank become more reluctant to offer indirect settlement when the risk of default if high. In addition to the scenarios arising from the settlement bank's profit function, a fifth case where $NNGG$ is the only candidate for market equilibrium can arise in the extended model. Thus, the settlement bank should attract both large banks to make a profit.

In each of these cases, the market solution is inefficient as it differs from the social planner's solution, see lemma 20 in the appendix. That is, the extended model replicates the results from the basic model without risk.

4.7 Conclusion

The model in this paper adds to the banking literature by building a model where the incentives of the banks and the settlement institutions are of importance.

There is a RTGS-system, which settle the gross amount of each individual payment. This payment system competes against a settlement bank in the market for settlement services. The settlement bank acts as intermediary as it facilitates payments between member banks and non-members of the RTGS-system. By assumption, the settlement bank is willing to serve demand from all banks. The settlement bank functions as a net settlement system. It nets out as many payments as possible before the remaining ones are settled via the RTGS-system.

Bot settlement institutions maximize profits via their price setting. There is sequential price settling such that the RTGS-system sets its price before the settlement bank does.

There are two large and two small banks, which demand settlement services from the RTGS-system or the settlement bank. Bilateral netting between banks are assumed away here. The choice of settlement institutions depends on costs. The costs of settlement in the RTGS-system include a membership fee and a fee per transaction. There is set-up costs related to the use of the RTGS-system, but not to access the services from the settlement bank. Thus, the cost of settlement by the settlement bank is a fee per transaction. The banks' choice of settlement institution depends on the costs of settlement within the RTGS-system and the settlement bank. The cost structure implies that large banks with a huge number of transactions tend to prefer a fixed fee and a low fee per transaction, i.e. large banks tend to prefer the RTGS-system. By the same logic, small banks tend to prefer the settlement bank.

The results show that three market equilibria can arise; 1) all banks settle indirectly via the settlement bank, 2) all banks settle directly within the RTGS-system or 3) large banks, which have many transactions, settle directly and small banks with few transactions settle indirectly. However, there are only two possible market equilibria, 1) and 2), when the settlement bank obtains a higher profit in 1) than in 3).

The market solution under sequential price setting where the RTGS-system is the first-mover is robust towards reversed sequential order where the settlement bank is the first-mover, but 3) is not an equilibrium under simultaneous price setting.

A comparison of the solutions reached by the market and the social planner shows a difference. In this sense, the market solution is inefficient. The structure of the settlement costs provides an explanation as it works like a kind of product differentiation. This allows the RTGS-system and the settlement bank to price above or equal to marginal costs depending on how many banks they serve with settlement services. A cost-covering RTGS-system reduces the inefficiency. A fully efficient market solution can be reached with a welfare-maximizing RTGS-system, but this is costly as subsidies and a different price setting for the RTGS-system are involved.

The model is extended by risk of illiquidity for the banks and the settlement bank. This implies that they can be unable to settle payments. The market solution changes in the extended model. Two additional situations can now arise. First, for a high risk of illiquidity, 2) and 3) are the only equilibria. That is, the settlement bank does not serve large banks. In the second situation, there is only one equilibrium, namely 4) large banks settle indirectly and the small banks settle within the payment system. The extended model reproduces the finding from the basic model of a difference between the market solution and the social planner's solution of the model. However, it is indeterminate whether the market solution is more efficient in the extended model. This is an interesting topic for further analysis.

Thus, the current model explains that indirect settlement can be an optimal choice for banks. We focus on the costs of settlements here. However, as touched upon above, there are other obstacles to achieve membership of a payment system. Restrictions on the nationality or size of the member banks of a national RTGS-system are examples of this. Settlement bank can facilitate the processing of payments by acting as intermediary between members and non-members of the payment system.

The model in this paper is set up with large-value payment systems, which handle interbank payments, in mind. However, it also applies to payment systems for retail payments or settlement of securities as the set up is relatively general. Furthermore, the model applies to other financial products. Some financial products, e.g. shares traded on a stock exchange, trade in a formal market place, whereas others are traded bilaterally between banks. The formal market place works like a payment system and the bilateral trade between agents as indirect settlement. In this case, indirect settlement takes place when agents use an intermediate agent (or network), which holds the asset on behalf of the seller and receives the payment from the buyer before the trade is finalized. That is, understanding the driving forces behind the banks' choice of settlement channels are important when evaluating whether the design of payment systems can improve.

4.8 References

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4.9 Appendix A: Equations in lemma 1

This section contains the price conditions for the five cases, which are excluded as equilibria by lemma 1. The expressions arise from comparison of each bank's profit from direct (G) and indirect (N) settlement in each of the five cases.

Case 2: $NGNN$. A small bank chooses G if

$$p_N - p_G = \frac{F}{2t} + r \tag{A1}$$

and a large bank choose N (G) if

$$p_N - p_G = \frac{F}{T+t} + r \tag{A2}$$

Case 4: $NNGN$. A large bank chooses G if (A2) is fulfilled and a small bank a small bank chooses G (N) if (A1) is fulfilled.

Case 7: $GGGN$. A large bank will choose N if (A2) is fulfilled and a small bank will choose G (N) if (A1) is fulfilled.

Case 8: $NGGG$. A large bank chooses G (N) if (A2) is fulfilled and a small bank chooses N if (A1) is fulfilled.

Case 9: $NGGN$. A large bank chooses G if (A2) is fulfilled and a small bank chooses N if (A1) is fulfilled.

4.10 Appendix B: Risk of illiquidity

The settlement bank and the banks can now become illiquid with probability η respectively β, $\eta, \beta \in [0, 1]$. As mentioned above, we denote this situation by the term default in the following. The assumption of equal probability of default for large and small banks is realistic for a symmetric financial shock. Note that the banks and the settlement bank are solvent when they are illiquid. This implies that the banks default if their counterparty has not collateralized its transactions.

4.10.1 Candidates for equilibrium

The banks' choice of settlement institution depends both on the costs of settlement and on the risk of default, see table B1. In line with the basic model, five of the cases can be eliminated as market equilibrium.

Lemma 15 *Five of the cases, $NGNN$, $NNGN$, $GGGN$, $NGGG$ and $NGGN$, can only be equilibrium if*

$$p_G = p_T - r - \frac{F}{2t} + x\left(p_N - p_T\right) \tag{B1}$$

$$p_G = p_T - r - \frac{F}{T+t} + x\left(p_N - p_T\right) \tag{B2}$$

where $x = \frac{1-\eta}{1-2\beta(1-\beta)}$ *or* $x = (1-\beta)^i$*, i=1,2,3.*

Proof. (B1) and (B2) arise from comparing the banks' profit expressions in $NGNN$, $NNGN$, $GGGN$, $NGGG$ and $NGGN$.

Case 2: $NGNN$. One can show that a small bank in this case chooses G instead of N if

$$p_G = p_T - r - \frac{F}{2t} + (1-\beta)^2\left(p_N - p_T\right) \tag{B3}$$

A large bank, which in this case chose N, chooses G instead if

$$p_G = p_T - r - \frac{F}{T+t} + (1-\beta)^2\left(p_N - p_T\right) \tag{B4}$$

whereas a large bank, which in this case chose G, chooses N instead if $p_G = p_T - r - \frac{F}{T+t} + (1-\beta)^3\left(p_N - p_T\right).$

Case 4: $NNGN$. A large bank chooses G instead of N if (B4) is fulfilled and a small bank, which in this case chose N, chooses G instead if (B3) is fulfilled. A small bank, which in this case chose G, chooses N instead if $p_G = p_T - r - \frac{F}{2t} + (1-\beta)^3\left(p_N - p_T\right).$

Case 7: $GGGN$. A large bank chooses N instead of G if

$$p_G = p_T - r - \frac{F}{T+t} + (1-\beta)\left(p_N - p_T\right) \tag{B5}$$

A small bank, which in this case chose G, chooses N instead if

$$p_G = p_T - r - \frac{F}{2t} + (1-\beta)(p_N - p_T) \tag{B6}$$

A small bank, which in this case chose N, chooses G instead if $p_G = p_T - r - \frac{F}{2t} + \frac{1-\eta}{1-2\beta(1-\beta)}(p_N - p_T)$.

Case 8: NGGG. A large bank, which in this case chose N, chooses G instead if $p_G = p_T - r - \frac{F}{T+t} + \frac{1-\eta}{1-2\beta(1-\beta)}(p_N - p_T)$. A large bank, which in this case chose G, chooses N instead if (B5) is fulfilled. One of the small banks in this case chooses N instead of G if (B6) is fulfilled.

Case 9: NGGN. A large bank, which in this case chose N (G), chooses G (N) instead if (B5) [(B4)] is fulfilled. A small bank, which in this case chose N (G), chooses G (N) instead if (B6) [(B3)] is fulfilled.

Thus, in each of these cases either the RTGS-system or the settlement bank will set an infinitesimally lower price and capture a larger fraction of the market for settlement services as in lemma 1. The equilibrium will thereby shift to either $NNNN$, $GGGG$, $GGNN$ or $NNGG$. ■

4.10.2 Market equilibrium

We will show that there are five different scenarios to consider for the market equilibrium. This follows from the binding price restrictions and the profit function for the settlement bank. As above, the price restriction is binding for the smallest (largest) banks in $GGGG$ ($NNNN$), i.e.

$$p_G \leq \frac{(1-\eta)(1-\beta)(p_N - p_T)}{1-2\beta(1-\beta)} + p_T - \frac{F}{2t} - r \tag{B7}$$

$$p_G \geq (1-\beta)^3 (p_N - p_T) + p_T - \frac{F}{T+t} - r \tag{B8}$$

There are two binding price restrictions in $GGNN$ given by the inequalities (B1) and (B2) with reversed inequality signs. These conditions reflect that small banks find it optimal to choose the settlement bank and large banks the RTGS-system.

Table B1: Profit expressions for the banks with risk of default

	Case	Large bank, $\pi^j_{L,i}$	Small bank, $\pi^j_{S,i}$
1	GGGG	$\pi^G_{L,i}$=$(1-\beta)(1-2\beta(1-\beta)((T+t)(p_T-p_G-r)-F)$	$\pi^G_{S,i}$=$(1-\beta)(1-2\beta(1-\beta)(2t(p_T-p_G-r)-F)$
2	NGNN,GNNN	$\pi^G_{L,1}$=$(1-\eta)(1-\beta)((T+t)(p_T-p_G-r)-F)$ $\pi^N_{L,2}$=$(1-\eta)(1-\beta)^3(T+t)(p_T-p_N)$	$\pi^N_{S,i}$=$(1-\eta)(1-\beta)^3 2t(p_T-p_N)$
3	GGNN	$\pi^G_{L,i}$=$(1-\eta)(1-\beta)((T+t)(p_T-p_G-r)-F)$	$\pi^N_{S,i}$=$(1-\eta)(1-\beta)^2 2t(p_T-p_N)$
4	NNGN,NNNG	$\pi^N_{L,i}$=$(1-\eta)(1-\beta)^3(T+t)(p_T-p_N)$	$\pi^G_{S,1}$=$(1-\eta)(1-\beta)(2t(p_T-p_G-r)-F)$ $\pi^N_{S,2}$=$(1-\eta)(1-\beta)^3 2t(p_T-p_N)$
5	NNGG	$\pi^N_{L,i}$=$(1-\eta)(1-\beta)^2(T+t)(p_T-p_N)$	$\pi^G_{S,i}$=$(1-\eta)(1-\beta)(2t(p_T-p_G-r)-F)$
6	NNNN	$\pi^N_{L,i}$=$(1-\eta)(1-\beta)^4(T+t)(p_T-p_N)$	$\pi^N_{S,i}$=$(1-\eta)(1-\beta)^4 2t(p_T-p_N)$
7	GGGN,GGNG	$\pi^G_{L,i}$=$(1-\eta)(1-\beta)((T+t)(p_T-p_G-r)-F)$	$\pi^G_{S,1}$=$(1-\eta)(1-\beta)(2t(p_T-p_G-r)-F)$ $\pi^N_{S,2}$=$(1-\eta)(1-\beta)2t(p_T-p_N)$
8	GNGG,NGGG	$\pi^G_{L,1}$=$(1-\eta)(1-\beta)((T+t)(p_T-p_G-r)-F)$ $\pi^N_{L,2}$=$(1-\eta)(1-\beta)(T+t)(p_T-p_N)$	$\pi^G_{S,i}$=$(1-\eta)(1-\beta)(2t(p_T-p_G-r)-F)$
9	GNNG,NGGN NGNG,GNGN	$\pi^G_{L,1}$=$(1-\eta)(1-\beta)((T+t)(p_T-p_G-r)-F)$ $\pi^N_{L,2}$=$(1-\eta)(1-\beta)^2(T+t)(p_T-p_N)$	$\pi^G_{S,1i}$=$(1-\eta)(1-\beta)(2t(p_T-p_G-r)-F)$ $\pi^N_{S,2}$=$(1-\eta)(1-\beta)^2 2t(p_T-p_N)$

Note: $i = 1, 2$ and $j = G, N$. Banks only pay fees for submitted payments.

Two binding price restrictions are required in $NNGG$ such that large banks settle indirectly and small banks settle within the RTGS-system

$$
\begin{aligned}
p_G &\geq \frac{(1-\eta)(1-\beta)(p_N - p_T)}{1-2\beta(1-\beta)} + p_T - \frac{F}{T+t} - r && \text{(B9)} \\
p_G &\leq (1-\beta)^3 (p_N - p_T) + p_T - \frac{F}{2t} - r && \text{(B10)}
\end{aligned}
$$

The RTGS-system only obtains profits when neither the banks settling indirectly nor the settlement bank default(s), e.g.

$$
\begin{aligned}
\pi_G^{GGGG} &= (1-\beta)(2-3\beta^2(1-\beta))(T+3t)(p_G - c_G) \\
\pi_G^{GGNN} &= (2T+4t-(2T+2t)\beta)(1-\eta)(p_G - c_G) \\
\pi_G^{NNNN} &= 0 \\
\pi_G^{NNGG} &= (6t-4t\beta)(1-\eta)(p_G - c_G)
\end{aligned}
$$

The settlement bank only obtains a profit when none of the banks or the settlement bank itself defaults. That is,

$$
\begin{aligned}
\pi_N^{GGGG} &= 0 \\
\pi_N^{GGNN} &= (1-\eta)(1-\beta)^2 \left[4t(p_N - c_N) - 2t(p_G + r) - F\right] \\
\pi_N^{NNNN} &= (1-\eta)(1-\beta)^4 (2T+6t)(p_N - c_N) \\
\pi_N^{NNGG} &= (1-\eta)(1-\beta)^2 \left[(2T+2t)(p_N - c_N) - 2t(p_G + r) - F\right]
\end{aligned}
$$

We can now proof that $NNGG$ cannot be equilibrium at the same time as $GGGG$, $GGNN$ and $NNNN$ are candidates for equilibrium.

Proposition 16 *Either NNGG or GGGG, GGNN and NNNN are candidates for equilibrium*

Proof. $NNGG$, $GGGG$, $GGNN$ and $NNNN$ are not candidates for equilibrium at the same time as the binding price restrictions in (B1)-(B4) are only fulfilled simultaneously if $2t \geq T+t$. But this is not fulfilled as $T > t$. This implies that either $NNGG$ or $GGGG$, $GGNN$ and $NNNN$ are candidates for equilibrium. ■

In contrast to the basic model, $NNGG$ can now arise in equilibrium, see proposition

1. However, this requires that (B3) and (B4) are fulfilled with equality, i.e.

$$\begin{aligned} p_N &= p_T + \frac{(1-2\beta(1-\beta))(T-t)F}{\left((1-\beta)^2(1-2\beta(1-\beta))-(1-\eta)\right)(1-\beta)2t(T+t)} \\ p_G &= \left(1+(1-\beta)^3\right)p_T - r - \frac{F}{2t} \\ &\quad + \frac{(1-\beta)^2(1-2\beta(1-\beta))(T-t)}{\left[(1-\beta)^2(1-2\beta(1-\beta))-(1-\eta)\right]2t(T+t)}F \end{aligned} \tag{B11}$$

Thus, there's only one possible price pair in this equilibrium and it must fulfill the non-negativity constraints in $NNGG$ such that both the banks and the settlement institutions obtain a non-negative profit, e.g. $p_T - r - \frac{F}{2t} \geq p_G \geq c_G$ and $p_T \geq p_N \geq c_N + \frac{t}{T+t}(p_G + r) + \frac{F}{2T+2t}$. $p_T - r - \frac{F}{2t} \geq p_G \Leftrightarrow p_T + \frac{1-2\beta(1-\beta)}{(1-\beta)^3(1-2\beta(1-\beta))-(1-\eta)(1-\beta)}\frac{T-t}{2t(T+t)}F < 0$ is fulfilled when $\eta \approx \beta$. One can show that $p_T \geq p_N$ is also fulfilled when $p_T - r - \frac{F}{2t} \geq p_G$ is fulfilled. As we discussed earlier on, the RTGS-system and the settlement bank price above marginal costs when they have market power on a subset of the market, e.g. $p_G \geq c_G$ and $p_N \geq c_N + \frac{t}{T+t}(p_G + r) + \frac{F}{2T+2t}$ will be fulfilled.

The settlement bank's choice

The possible scenarios in market equilibrium are:

1. $GGGG$, $GGNN$ and $NNNN$ are candidates for equilibrium when (B12) and (B13) are fulfilled.

2. $GGGG$ and $NNNN$ are candidates for equilibrium when (B12) is fulfilled and (B13) is violated.

3. $GGGG$, $GGNN$ and $NNNN$ are candidates for equilibrium when (B12) and (B13) do not hold.

4. $GGGG$ and $GGNN$ are candidates for equilibrium when (B12) is violated and (B13) is fulfilled.

5. $NNGG$ is candidate for equilibrium.

The first four scenarios are due to the slope and intercept of the settlement bank's profit functions when $GGGG$, $GGNN$ and $NNNN$ are candidates for equilibrium, see lemma 13 and 14. This corresponds to lemma 2 and 3 in the basic model. Scenario 1 and

2 can be illustrated as in figure 4.1a and 4.2a. Scenario 3 and 4 are illustrated in figure B1. These cases only arise when the probability of bank default is high and it's quite intuitive that the settlement bank tends to limit the losses it is exposed to by offering settlement services to the smallest banks only. The fifth scenario, where $NNGG$ is the market solution, follows from proposition 4.

Lemma 17 *The slope of π_N^{NNNN} is larger than the slope of π_N^{GGNN} for low values of β*

Proof. It follows from π_N^{NNNN} and π_N^{GGNN} that for β-values below ≈ 0.35

$$4t \leq (2T + 6t)(1 - \beta)^2 \Leftrightarrow \beta \leq 1 - \sqrt{\frac{t}{T + 3t}} \tag{B12}$$

■

Lemma 18 *π_N^{NNNN} intersects the profit-axis at a smaller profit-value than π_N^{GGNN} if the c_N is high enough*

Proof. It follows from π_N^{NNNN} and π_N^{GGNN} that

$$\begin{aligned} -2t(p_G + r) - 4tc_N - F &\leq -(1-\beta)^2 (2T + 6t)\, c_N \Leftrightarrow \\ c_N &\geq \frac{2t(p_G + r) + F}{(1-\beta)^2 (2T + 6t) - 4t} \end{aligned} \tag{B13}$$

■

The RTGS-system's choice

The RTGS-system's profit function differs from the profit function in the basic model see figure B2 and lemma 15.

Lemma 19 *$\pi_G^{GGGG} \geq \pi_G^{GGNN}$ if β and η are small enough*

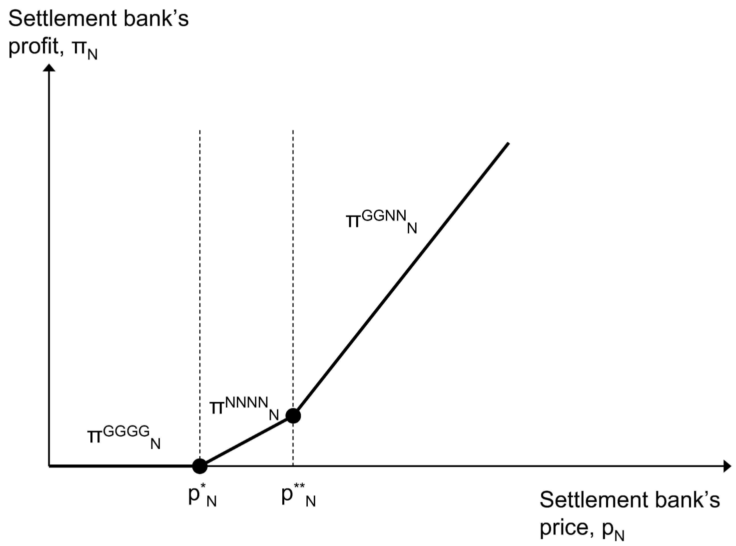
Proof. The condition required for $\pi_G^{GGGG} \geq \pi_G^{GGNN}$ is

$$(1-\beta)(2 - 3\beta^2(1-\beta))(T + 3t) \geq ((1-\beta)(2T + 2t) + 2t)(1 - \eta) \tag{B14}$$

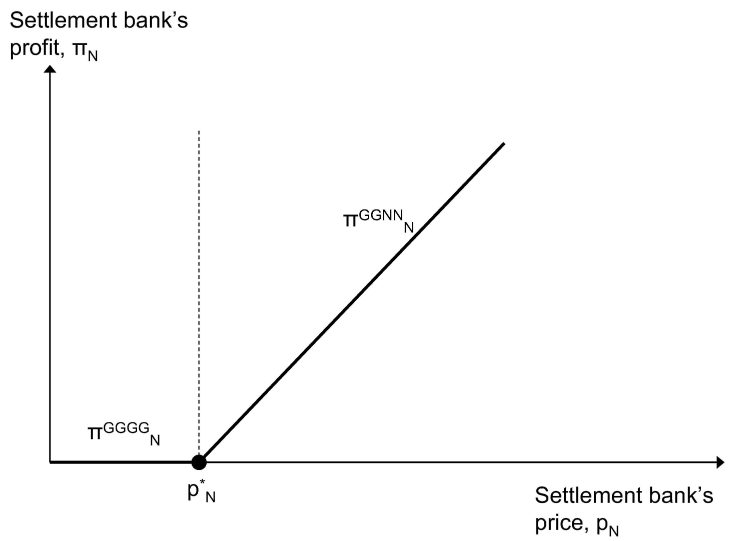
This is fulfilled for small values of β and η. ■

As above, the RTGS-system's profit in each of the possible equilibria determines the market equilibrium. In scenario 1 and 3 when (B14) is fulfilled, the RTGS-system

Figure B1: Settlement bank's profit function in scenario 3 and 4



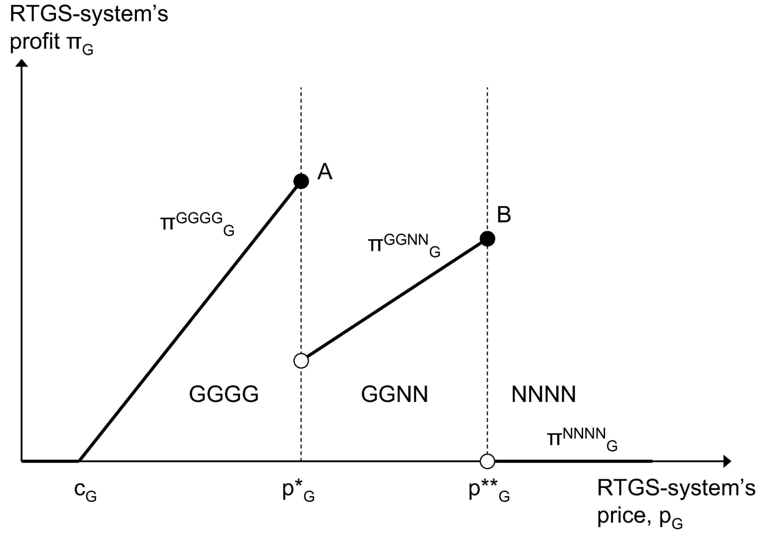
(a) Scenario 3



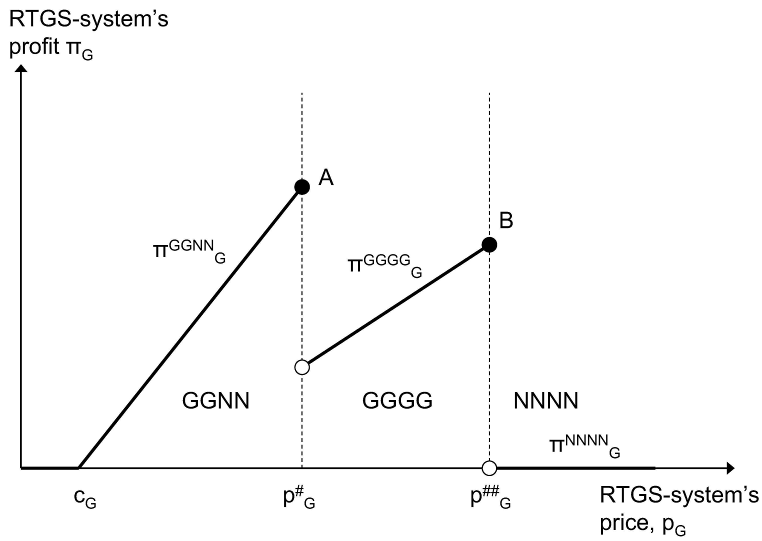
(b) Scenario 4

Note: Scenario 1 and 2 are illustrated in figure 1a respectively 2a.

Figure B2: RTGS-system's profit and price



(a) $\pi_G^{GGGG} \geq \pi_G^{GGNN}$



(b) $\pi_G^{GGGG} < \pi_G^{GGNN}$

sets the price p_G^{1R} in $GGGG$ according to (B7) and (B8). The RTGS-system's price in $GGNN$, p_G^{2R}, must fulfill $\pi_N^{GGNN}(p_G^{2R}) = \pi_N^{NNNN}(p_G^{2R})$ if the settlement bank should accept $GGNN$ as the equilibrium. In scenario 1 and 3 when (B14) is violated, p_G^{1R} must fulfill $\pi_N^{NNNN}(p_G^{1R}) = \pi_N^{GGGG}(p_G^{1R})$ and p_G^{2R} is set in accordance with (B7) and (B8). In scenario 2, the RTGS-system charges the same price in $GGGG$ as in scenario 1 and 3.

The RTGS-system has more market power in scenario 4 than in scenario 1-3 as the settlement bank only offers settlement services to small banks. When (B14) is fulfilled, the RTGS-system charges p_G^{1R}, which fulfils $\pi_N^{GGNN}(p_G^{1R}) = \pi_N^{GGGG}(p_G^{1R})$ in $GGGG$ and p_G^{2R} according to the binding price restriction in $GGNN$. When (B14) is violated, p_G^{1R} is set in accordance with the binding price restrictions in $GGGG$ and p_G^{2R} fulfils $\pi_N^{GGNN}(p_G^{2R}) = \pi_N^{GGGG}(p_G^{2R})$ in $GGNN$.

4.10.3 Welfare and the inefficient market solution

The social planner considers deposit insurance when defaults can arise. The deposit insurance is equal to λ times the loss given default and bails out the banks' customers in case of default. The social planner maximizes the total welfare, which is equal to the profits for the banks, the RTGS-system and the settlement bank minus the premium on the deposit insurance.

$$
\begin{aligned}
W^{NNNN} &= \left(1-\lambda\eta\left(1-\beta\right)^4\right)\left(2T+6t\right)\left(p_T-c_N\right) \\
&\quad -\lambda\beta\left(2-\beta\right)\left(2+\beta^2-2\beta\right)\left(2T+6t\right)\left(p_T-c_N\right) \\
W^{GGNN} &= \left(1-\beta\lambda-\eta\lambda\left(1-\beta\right)\right)\left(\left(2T+2t\right)\left(p_T-c_G-r\right)-\left(3-\beta\right)F\right) \\
&\quad -2t\left(1-\eta\lambda\right)\left(c_G+r\right)+2t\beta\lambda\left(1-\eta\right)\left(2-\beta\right)\left(p_G^{2R}+r\right) \\
&\quad +\left(1-\beta\lambda\left(2-\beta\right)-\eta\lambda\left(1-\beta\right)\right)4t\left(p_T-c_N\right) \\
W^{GGGG} &= \lambda\beta\left(1-\beta\right)^2\left(4-3\beta\right)\left(T+3t\right)\left(p_G^{1R}-c_G\right) \\
&\quad +\left(1-\beta\lambda-2\beta\lambda\left(1-\beta\right)^2\right)\left(2\left(T+3t\right)\left(p_T-r-c_G\right)-4F\right) \\
W^{NNGG} &= \left(1-\beta\lambda-\eta\lambda\left(1-\beta\right)\right)\left(4t\left(p_T-c_G-r\right)-\left(3-\beta\right)F\right) \\
&\quad -2t\left(1-\eta\lambda\right)\left(c_G+r\right)+2t\beta\lambda\left(1-\eta\right)\left(2-\beta\right)\left(p_G^{3R}+r\right) \\
&\quad +\left(1-\beta\lambda\left(2-\beta\right)-\eta\lambda\left(1-\beta\right)\right)\left(2T+2t\right)\left(p_T-c_N\right)
\end{aligned}
$$

where p_G^{iR} for $i = 1, 2$ is the RTGS-system's price in $GGGG$ respectively $GGNN$. These prices are derived in a similar way as in the basic model as explained above. p_G^{3R} is the

RTGS-system's price in $NNGG$ given by (B11). Note that p_G^{1R}, p_G^{2R} and p_G^{3R} drop out of the welfare expressions when only the settlement bank can default ($\beta = 0$). Furthermore, W^{GGGG} does not depend on η, e.g. there is no settlement bank when all banks settle via the RTGS-system.

The market solution is inefficient in the sense that it differs from the social planner's solution as the following lemma shows. This result is in line with the findings from the basic model. The market inefficiency in the extended model can be illustrated as in figure 4.3.

Lemma 20 *The market solution in the model with risk of default is inefficient in the sense that it differs from the social planner's solution*

Proof. The inefficiency follows from the fact that (B15)-(B18) differ from (B19)-(B22). A comparison of the welfare expressions give

$$\begin{aligned} W^{GGGG} &\geq W^{NNNN} \Leftrightarrow \qquad\qquad \text{(B15)} \\ p_G^{1R} &\geq c_G + \frac{1-\beta\lambda-2\beta\lambda\left(1-\beta\right)^2}{\beta\lambda\left(1-\beta\right)^2\left(4-3\beta\right)}2\left(c_G+r-p_T+\frac{2F}{T+3t}\right) \\ &\quad +2\left(p_T-c_N\right)\frac{1-\eta\lambda\left(1-\beta\right)^4-\beta\lambda\left(2-\beta\right)\left(2+\beta^2-2\beta\right)}{\beta\lambda\left(1-\beta\right)^2\left(4-3\beta\right)} \end{aligned}$$

$$\begin{aligned} W^{GGNN} &\geq W^{NNNN} \Leftrightarrow \qquad\qquad \text{(B16)} \\ p_G^{2R} &\geq -r+\left(c_G+r\right)\frac{\left(2T+4t\right)\left(1-\eta\lambda\right)-\beta\lambda\left(1-\eta\right)\left(2T+2t\right)}{2t\beta\lambda\left(1-\eta\right)\left(2-\beta\right)} \\ &\quad +\frac{1-\beta\lambda-\eta\lambda\left(1-\beta\right)}{2t\beta\lambda\left(1-\eta\right)\left(2-\beta\right)}\left(\left(3-\beta\right)F-2\left(T+t\right)p_T\right) \\ &\quad +\left(p_T-c_N\right)\frac{\left(T+t\right)\left(4-4\beta+\beta^2\right)}{t\beta\lambda\left(1-\eta\right)\left(2-\beta\right)} \\ &\quad -\left(p_T-c_N\right)\frac{\eta\left(1-\beta\right)^4\left(T-t\right)+2t\left(1-\beta\right)\left(\eta-2\beta+\beta^2\right)}{t\beta\left(1-\eta\right)\left(2-\beta\right)} \end{aligned}$$

$$\begin{aligned}
W^{GGGG} &\geq W^{GGNN} \Leftrightarrow \\
&\lambda\beta\left(1-\beta\right)^{2}\left(4-3\beta\right)\left(T+3t\right)\left(p_{G}^{1R}-c_{G}\right) \\
&-2t\beta\lambda\left(1-\eta\right)\left(2-\beta\right)\left(p_{G}^{2R}+r\right) \\
&\geq \left(\left(1+\beta\right)\left(1-\beta\lambda\right)-\lambda\left(1-\beta\right)\left(8\beta\left(1-\beta\right)-\eta\left(3-\beta\right)\right)\right)F \\
&+\left(c_{G}+r\right)2t\left(1-2\beta\lambda+\eta\lambda\right) \\
&+\left(c_{G}+r\right)2\lambda\left(1-\beta\right)\left(\eta\left(T+t\right)-2\beta\left(1-\beta\right)\left(T+3t\right)\right) \\
&-4t\left(1-\beta\lambda\left(2-\beta\right)-\eta\lambda\left(1-\beta\right)\right)c_{N} \\
&+2\lambda\left(1-\beta\right)\left(\left(T+3t\right)\left(2\beta\left(1-\beta\right)-\eta\right)-\beta 2t\right)p_{T}
\end{aligned} \tag{B17}$$

$$\begin{aligned}
W^{NNGG} &\geq 0 \Leftrightarrow \\
p_{G}^{3R} &\geq -r+\frac{1-\eta\lambda}{\beta\lambda\left(1-\eta\right)\left(2-\beta\right)}\left(c_{G}+r\right) \\
&-\frac{\left(1-\beta\lambda\left(2-\beta\right)-\eta\lambda\left(1-\beta\right)\right)}{t\beta\lambda\left(1-\eta\right)\left(2-\beta\right)}\left(T+t\right)\left(p_{T}-c_{N}\right) \\
&-\frac{\left(1-\beta\lambda-\eta\lambda\left(1-\beta\right)\right)\left(4t\left(p_{T}-c_{G}-r\right)-\left(3-\beta\right)F\right)}{2t\beta\lambda\left(1-\eta\right)\left(2-\beta\right)}
\end{aligned} \tag{B18}$$

A comparison of the RTGS-system's profit expressions give:

$$\pi_{G}^{GGGG} \geq \pi_{G}^{NNNN} \Leftrightarrow p_{G}^{1R} \geq c_{G} \tag{B19}$$

$$\pi_{G}^{GGNN} \geq \pi_{G}^{NNNN} \Leftrightarrow p_{G}^{2R} \geq c_{G} \tag{B20}$$

$$\begin{aligned}
\pi_{G}^{GGGG} &\geq \pi_{G}^{GGNN} \\
&\left(1-\beta\right)\left(2-3\beta^{2}\left(1-\beta\right)\right)\left(T+3t\right)\left(p_{G}^{1R}-c_{G}\right) \\
&\geq \left(1-\eta\right)\left(\left(1-\beta\right)\left(2T+2t\right)+2t\right)\left(p_{G}^{2R}-c_{G}\right)
\end{aligned} \tag{B21}$$

$$\pi_{G}^{NNGG} \geq 0 \Leftrightarrow p_{G}^{3R} \geq c_{G} \tag{B22}$$

■

Chapter 3

Financial Soundness in Danish Banks: Does the Composition of Customers Matter?

I thank Danmarks Nationalbank for providing the data set for the analysis and I'm especially grateful to Mads Kristoffersen in this connection. I thank associate professor Søren Leth-Petersen, professor Thomas Rønde and professor Hans Christian Kongsted for helpful comments and suggestions during the preparation of this paper. I'm grateful to Kathrine Thrane Bløcher, Michala Ehlers Rasmussen and Lars Jul Overby for comments to earlier versions of this paper. The views expressed do not necessarily reflect the views of Danmarks Nationalbank.

Abstract

Using unique micro-level data for Danish banks' lending and deposits subdivided into industries (Real estate activities and renting, Farming, Building and construction, Wholesale except motor vehicles etc.) or sectors (Households, Firms, Government and MFIs) over the period from 2000 to 2008 we find empirical evidence that the customer composition matter for the financial soundness of banks. The financial soundness is measured by the Z-score technique and we control for bank specific factors and the macroeconomic development.

Specifically, the lending to assets for Building and construction and Sale of motor vehicles and automotive fuel for the industries have a positive impact on the financial soundness of banks. For the sectors, the lending to Households has a significant and positive effect. The impact of the customer composition on the financial soundness is surprisingly small both for industries and for sectors. What really matters is business cycle effects and the bank size.

To my knowledge, this is the first paper that analyzes the relationship between the banks' financial soundness and their lending to specific industries and sectors. This paper adds to the literature on the financial soundness of banks in this respect.

Version: April 2010

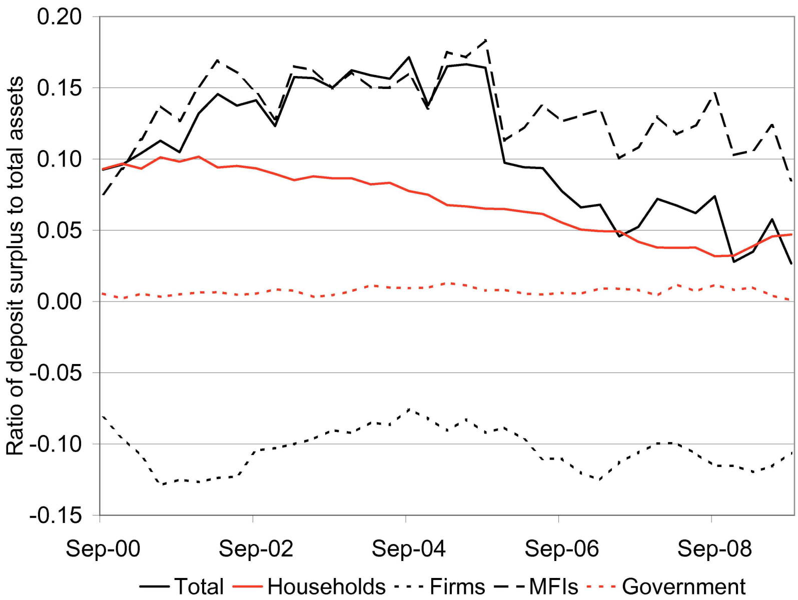
Keywords: Financial Stability, Banking Regulation

JEL classification: G18, G21

Introduction

Traditionally, banks in Denmark have financed their lending by deposits from firms and households. However, the lending has grown much more than deposits recently, see figure 5.1. The decreasing deposit surplus makes the banks more sensitive towards leverage risks. Leverage risk implies that the more a bank has lend out relative to capital held, the smaller losses can it bear.

Figure 5.1: Deposit surplus for banks



Source: MFI-statistics for all Danish banks

The leverage risk has been mentioned in relation to lending to specific industries and sectors. In the aftermath of the financial crisis, the Danish authorities have facilitated public ownership in a number of banks. Two of these banks, Roskilde Bank A/S and EBH Bank A/S, have been highly exposed towards the real estate market. Moreover, a number of banks in Denmark have obtained individual government guarantees for existing and new unsubordinated, unsecured debt. At the same time, the authorities have warned the banks against concentrating their loan portfolios in certain sectors or industries. The market for real estate and lending to farmers are mentioned as two of the critical industries, but loans to households or employees might also become critical for the banks' financial stability if the market for residential property freezes during an economic downturn, see DFSA (2009a). Recently, the banks have decreased the total amount lend to customers. This action is in line with the response by the banks during the latest Danish banking crisis in the beginning of the 1990's.

Thus, the financial crisis has highlighted the need for assessing the concentration of risks in banks, e.g. whether banks' exposure towards customers can "produce (i) losses large enough (...) to threaten a bank's creditworthiness or ability to maintain its core operations or (ii) a material change in a bank's risk profile", see BCBS (2009, p. 15). The Basel Committee notes that one of the typical situations where risk concentrations can apply is for certain industries or sectors.

This paper focuses on the leverage risk among Danish banks and analyzes to what extent the composition of banks' loans against specific industries or sectors influences their financial soundness. There are 50 different industries (*Real estate activities and renting*, *Farming*, *Building and construction, Wholesale except motor vehicles* etc.) and 4 different sectors (*Households*, *Firms*, *Government* and *Monetary and financial institutions, MFIs*).

Other types of risk might influence the financial soundness of the banks, but these will not be considered here. However, a few comments will be devoted to the funding risk as it is closely related to the banks' lending activities. Funding risk is the risk that banks cannot obtain funding to maintain their banking activities. One of the ways to achieve the required funding is to borrow from banks with excess liquidity in the money market. During the financial crisis, the central bank has offered facilities to mitigate the shortfalls in the money market. Thus, although the banks can be exposed to other types of risks, this paper focuses solely on the influence of the leverage risk on the financial soundness of banks.

To my knowledge, this is the first paper that analyzes the relationship between the banks' financial soundness and their lending to specific industries and sectors. Other recent papers within this field analyze the relationship between competition in the banking sector and banks' financial soundness; see Uhde and Heimeshoff (2009) and Boyd et al. (2009). Fungáčová and Solanko (2008) find that bank size and foreign ownership has implications for the financial soundness of banks.

The data sets are unique. We have access to micro-level data for each bank's lending and deposits subdivided into sectors and industries during the period 2000-2008. The financial soundness of banks is measured by the Z-score technique. We control for bank-specific variables and macroeconomic indicators when we estimate the relation between the customer composition and the financial soundness of banks.

The first set of results is based on the data set on industries since this has the most detailed customer composition. We find that the lending to *Building and construction* and *Sale of motor vehicles and automotive fuel* affect the financial soundness of banks positively. However, the impact of customer composition for the industry dimension is surprisingly small. What really matters is business cycle effects and the bank size.

The results are relatively stable towards changes in the bank-specific variables or the macroeconomic indicators. However, the results are sensitive towards changing the measure of customer composition, i.e. replacing lending to assets by deposit surplus to assets.

These findings are largely confirmed by the estimations on the sectoral sample. Somewhat surprising, we find that the lending to *Households* affect the financial soundness of banks significantly along with the macroeconomic indicators and the size of the banks. We expect that the industries that matter for the financial soundness of banks correspond to the sectors, which have significant influence.

The remainder of this paper is build up as follows. Related studies of banks' financial soundness are discussed in section 5.1. Section 5.2 introduces the Z-score technique together with the explanatory variables and the econometric model. Section 5.3 and 5.4 are devoted to the econometric results for the two samples of customer composition for industries respectively sectors. Finally, section 5.5 concludes.

5.1 Related literature

The Z-score indicator has become a widely used proxy for banks' financial soundness. Boyd and Graham (1988) originally defined the Z-score. The idea with this measure is to combine different measures from the banks' accounts such that one measure can identify banks, which have a lower return than other banks in a sample. We will discuss related literature where the Z-score is used as a proxy for the financial soundness of banks here and come back to how the Z-score is defined and calculated in practice in the next section.

Uhde and Heimeshoff (2009) analyze whether the concentration of the banking sector affects the financial soundness of banks in 25 EU-countries. They use the Z-score as a proxy for financial soundness. Using a random effects model where they control for the macroeconomic development, bank-specific characteristics, regulatory and institutional factors, they show that an increase in the national banking market concentration has a negative impact on European banks' financial soundness. They suggest that the European Commission should evaluate systemic stability when it approves mergers between European banks, e.g. consider financial soundness both ex ante and ex post of cross-country mergers of banks.

The findings by Uhde and Heimeshoff (2009) thus confirm the view that although greater competition might be efficient, it decreases the financial stability of banks. Allen and Gale (2004) point out that the relationship between financial stability of banks and competition in the banking sector is more complex than this. It depends on the underlying theoretical models whether more competition increases the financial stability.

Boyd and De Nicoló (2005) show theoretically that the banks become more financially stable when competition increases if there is moral hazard. Moral hazard exists if firms increase their own risk of failure when banks raise loan rates. Without moral hazard, their model confirms the traditional view that increased competition worsens the financial stability of banks. There is empirical evidence of moral hazard effect, see Boyd et al. (2009). The current paper abstracts from competition and focuses on the relation between banks' financial stability and the composition of their loan portfolios.

Fungáčová and Solanko (2008) analyze the relationship between insolvency risk and location (Moscow-based or not), ownership (state-owned, privately owned, owned by foreigners) and size in a sample of Russian banks. Here, the Z-score is as a proxy for insolvency risk. They find that Moscow-based banks are more stable than other banks and that foreign-owned banks bear higher insolvency risk (have lower Z-scores) than domestic private banks. Note however that the latter result can be due to less capital held in subsidiary companies since additional capital is transferred from the parent company if needed. Fungáčová and Solanko (2008) also find that the dummy for state-owned banks has a positive effect on a bank's insolvency risk. Furthermore, their results suggest that larger banks have lower Z-scores.

Büyükkarabacak and Valev (2009) find that a strong growth in credit to households is a good indicator of banking crisis in a panel of 37 countries. Moreover, they argue that it is important to distinguish the lending to households from the lending to firms since the credit to households is larger than the credit to firms in many countries. The current paper considers this by dividing the banks' lending into specific sectors or industries.

Others have modelled the risk of bank failures explicitly. Andersen (2008) shows that an index for bank failure must include six different risk measures (capital adequacy ratio, ratio of residential mortgages to gross lending, expected loss measure, concentration risk measure, return on assets and a liquidity indicator) in a model of bank failure for Norwegian banks. By the end of this paper, we discuss the pros and cons of modelling the risk of bank default explicitly.

5.2 Empirical analysis

The customer composition divided into industries is in the data set on industries and divided into sectors in the sectoral data set. For a list of banks comprised by the samples, see table 5.1. The variables are defined in table 5.2. Table 5.5 and 5.15 report the summary statistics and table 5.6 and 5.21 the correlations between the explanatory variables in the preferred model specification.

5.2.1 Data

The samples comprise annual observations for 22 Danish banks during the years 2000-2008. These banks account for 84.3 per cent of the total assets in the Danish banking sector on average during the estimation period. The samples includes large and medium-sized banks, see table 5.1. All the banks do traditional banking business, e.g. "institutions whose current operations consist in granting loans and receiving deposits from the public", cf. Freixas and Rochet (1997, p. 1).

The sectoral data set is almost balanced, whereas the data set on industries is unbalanced. The unbalance is due to the required statistical reporting by the authorities, i.e. some banks have become bound to report their lending and deposits to specific industries during the sample period.

Some of the banks have merged during the estimation period and the data is corrected to account for this. Most mergers and take-overs are incorporated in accounting data immediately, whereas the statistical reporting continues for each of the merged units for a while. A typical reason is adjustments in the it-systems of the merged units.

There are two main data sources. The first is statistics on Danish banks' lending, deposits and total assets broken down by sector (sectoral data set) and industries (data set on industries) from the Danish central bank. Note that the central bank produces the statistics on banks' lending and deposits. The second data source is data from the banks' balance sheets made up by the end of December during the years 2000-2008. In addition, macroeconomic variables are obtained from Statistics Denmark.

5.2.2 Variables

Z-score

As already mentioned, the banks' financial soundness is measured by the Z-score technique. The Z-score is defined as

$$z = \frac{\mu + c}{\sigma}$$

where μ is the return on average assets before taxes (ROAA), c is the ratio of equity capital to total assets and σ is the standard deviation of ROAA (sdROAA). ROAA is a proxy for the banks' profitability and the standard deviation of it is a measure of return volatility. The ratio of equity capital to total assets is a measure of the banks' capital ratio. All of these measures can be calculated from publicly available accounting data for the banks. Thus, "the Z-score combines in one single indicator the banks' profitability, capital ratio and return volatility", see Uhde and Heimeshoff (2009, p. 1303). Figure 5.2 shows the Z-scores for the banks in the samples by the end of 2008.

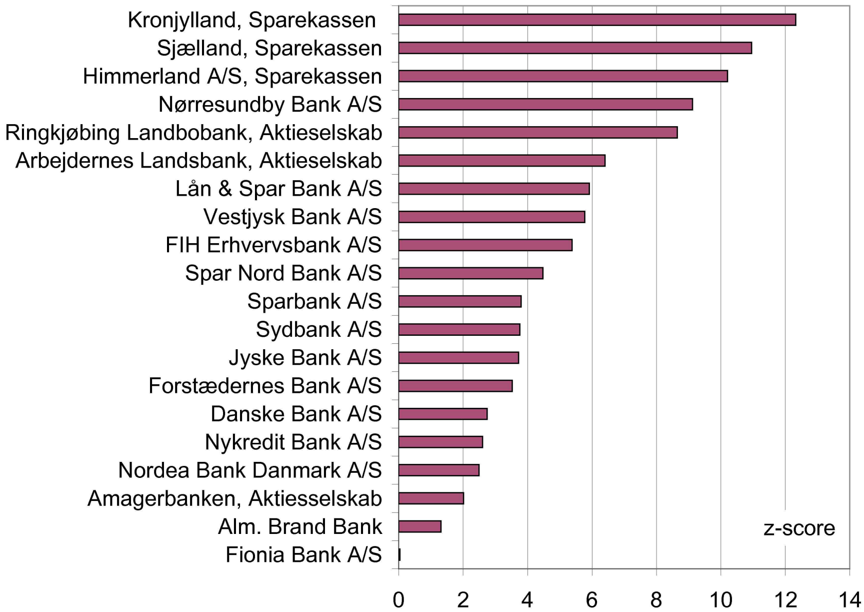
Ceteris paribus, banks with a low financial soundness (low Z-score) are closer to distress than banks with a high financial soundness. However, Fungáčová and Solanko (2008) find that larger banks tend to have lower Z-scores. Boyd et al. (2006, p. 25) note that banks with minimal variations in their earnings tend to have high Z-values. This suggests that even though the actual risks of financial distress changes for the banks, the Z-score indicator might not reflect this properly for banks of a certain size or with a stable profit over time. We consider this critique below by regressing each of the Z-score components on the preferred set of explanatory variables.

Customer composition by industries and sectors

The customer composition by industries is measured by the loans to assets ratio for the industries. That is, we estimate industry j's ratio of loans to total assets for each of the banks. However, there are 50 different categories of industries, see table 5.14. Thus, we select the 9 most important industries and collect the data for the remaining industries in a category labeled *Other industries* such that we include 10 variables for customer composition by industries in the estimations below. To start with, we consider the industries, which have the lowest deposit surplus to assets on average, as the most important for the banks' financial stability. The selected industries are shown in table 5.3.

The expected signs of the customer composition in industries are unknown. There

Figure 5.2: Z-scores by the end of 2008



are several reasons for this. First, industries like *Farming* and *Real estate activities and renting* can usually pose collateral in buildings and land. However, these industries are recently mentioned as risky both for distressed banks and for the banking sector in general; see DFSA (2009b) and annual accounts of Roskilde Bank A/S (2010) and EBH Bank A/S (2010). Second, although we expect that the banks grant loans to projects with an expected positive outcome, the actual outcome of these investments are uncertain due to changes in the business cycle, customer preferences in the goods market etc. Third, some of the industries might cover rather different economic activities. Note however that we have access to the most detailed statistics available for the industry dimension.

The customer composition is also measured by loans to assets in the sectoral data set for each of the four sectors. We include data for all four sectors in the estimations and table 5.16 shows the activities included in each sector. Note that *Firms* includes self-employed individuals since many farmers are registered as self-employed in the Danish statistics.

The expected signs of the customer composition by sectors are unknown. The categories in the sectoral sample are more aggregated than in the data set on industries and this makes it even more difficult to discuss expected signs a priori.

The lending to industries and sectors are related to the assets in order to correct for the bank size. That is, we are interested in the relative exposure for the banks towards specific industries and sectors. Initially we focus on the lending since the banks can affect their lending to specific industries and sectors directly. For instance, a bank can change its business strategy such that it lends less to risky customer groups. Below, we check how robust the results are if we also take the deposits of specific industries and sectors into account. Moreover, the sensitivity of the results with respect to a different selection criterion for the most important industries is considered in the data set on industries.

Further explanatory variables

We include five different variables to control for the characteristics of each bank; loan loss provision, size, growth in loans, cost-income ratio and large exposures[1]. Since we include the same explanatory variables with respect to bank characteristics and business cycle indicators in the estimations on both samples below, we comment on the expected signs of these variables here.

Loan loss provision to total assets (loan loss provision hereafter) is a common measure of the banks' credit risk and the quality of the loan portfolio of banks, see Uhde and Heimeshoff (2009) and Boyd et al. (2009). Loan loss provisions are only reported by banks if they expect that some of their customers do not service their debt as agreed upon. Moreover, loan loss provisions has been subdivided from provisions in total in the banks' accounts from 2005 and onwards due to a change in the regulation of the banking sector in Denmark. Together, this explains the low number of observations (78 observations out of 196) in table 5.15. We expect that the loan loss provisions affect the Z-score negatively.

Since the size of the Danish banks differ considerably, it is important to include this in the analysis. Size is measured by the natural logarithm of bank i's total assets in the data set on industries. This is a common measure in the literature, see Fungáčová and Solanko (2008) and Boyd et al. (2009). In the sectoral data set, bank size is captured by banks' share of total assets, i.e. we estimate bank i's share of total assets for the whole

[1]In addition to these measures, the net interest margin is often included among the variables capturing bank characteristics, see Uhde and Heimeshoff (2009) and Akhter and Daly (2009). The net interest margin is defined as a bank's interest income as a share of its interest-bearing assets. In both samples of Danish banks, the net interest margin seems to cause multicollinearity and it is therefore excluded in the estimations.

banking sector in each period. The reason for the replacement of the size variable in the sectoral data set is the partial correlation coefficient between the explanatory variables. We come back to this below. As mentioned previously, larger banks tend to have lower Z-scores so we expect that the bank size affects the banks' financial soundness negatively.

The growth in loans captures the pace at which the banks grow. The growth in loans tends to vary with the GDP-growth. Around half of the largest decreases in growth in loans occur in the recession by the end of 2008 or later, whereas the growth in loans increases the most during the boom in 2005-2006. However, a high growth rate in lending can also be due to a change in a bank's business strategy. The sign of growth in loans is therefore indeterminate.

It is also common to include the cost-income ratio among the bank-specific variables. It measures how effectively the banks are driven and we expect a negative impact on the Z-score from the cost-income ratio. Notice that the cost-income ratio varies substantially between banks, see table 5.5.

Large exposures is defined as the sum of assets and off-balance-sheet items that, after a reduction for secured exposures, exceeds 10 % of the bank's capital. We divide the sum of large exposures by assets in the estimations (abbreviated as large exposures from now on). Large exposures measure the concentration of the loan portfolio. The more concentrated the loan portfolio is, the more vulnerable are the banks towards the quality of their engagements. Lending to high-quality projects can give high returns and vice versa for low-quality engagements. Moreover, concentration is important for financial stability according to the Basel II-regulation, see BCBS (2009). Therefore, the expected sign of large exposures is negative.

The banks' business activity depends on the business cycle. At the beginning of the sample period, the Danish economy was slowing down and the growth rate in GDP was below potential in the years 2001-2003. The economy took off thereafter and lasted until the end of 2008. The financial crisis caused the GDP growth rate to collapse by the end of 2008.

Annual growth rates of real GDP and inflation capture the overall macroeconomic development. Uhde and Heimeshoff (2009) and Boyd et al. (2009) use the same macroeconomic indicators and include the lagged real interest rate as well in their estimations. We exclude the lagged real interest rate here since it is highly correlated with the real GDP growth in our samples. Fungáčová and Solanko (2008) only include real GDP growth in their one-country sample of Russian banks. We expect that the GDP-growth affect the Z-score positively, whereas the sign of the inflation rate is indeterminate from the outset.

5.2.3 Econometric model

The estimations take the random effects (RE) and fixed effects (FE) models as the starting point using the following econometric model

$$\begin{aligned} y_{it} &= \mathbf{x}_{it}\boldsymbol{\beta} + u_{it} \\ \text{where } u_{it} &= c_i + v_{it} \end{aligned} \tag{5.1}$$

There are $i = 1, ..., 22$ banks and $t = 1, ..., T_i$ time periods. There are maximum 9 observations per bank. y_{it} is the Z-score and the explanatory variables in $\mathbf{x}_{it}$ include variables for the customer composition for sectors or industries, bank-specific variables, macroeconomic indicators and time dummies. We allow for a bank-individual effect c_i.

The Hausman test statistic is applied to determine whether the RE or FE model is appropriate in our samples. However, there are some caveats. First, the variance-covariance matrix of the standard Hausman test statistic is generally not positive definite in our samples. This implies that a key assumption underlying this test is unfulfilled. This often occurs in relatively small or finite samples, cf. Greene (2008, chapter 9). Therefore, we consider an alternative F-test as suggested by Baltagi (2005, chapter 4.3) and Wooldridge (2002, chapter 10). This is based on the augmented regression

$$\widetilde{y}_{it} = \widetilde{\mathbf{x}}_{it}\boldsymbol{\beta} + \ddot{\mathbf{x}}_{it}\boldsymbol{\eta} + w_{it} \tag{5.2}$$

where $\ddot{\mathbf{x}}_{it}$ are explanatory variables transformed for the FE-model and $\widetilde{y}_{it}$ and $\widetilde{\mathbf{x}}_{it}$ are transformed for the RE-model[2] and w_{it} is an error term. We test whether the fixed effects estimates can be excluded from the random effects model without altering the consistency of the random effects estimates, e.g. $H_0 : \boldsymbol{\eta} = 0$. Only variables that vary across banks are included in this test.

Second, there are rather few observations in the sample. This might imply that the

[2] The mean values for each bank are subtracted from the variables in the FE model. That is, the FE model is $\ddot{y}_{it} = \ddot{\mathbf{x}}_{it}\boldsymbol{\beta} + \ddot{u}_{it}$where $\ddot{y}_{it} = y_{it} - \frac{1}{T_i}\sum_{t=1}^{T_i} y_{it} = y_{it} - \overline{y}_{it}$ etc. The variables in the RE model, $\widetilde{y}_{it} = \widetilde{\mathbf{x}}_{it}\boldsymbol{\beta} + \widetilde{u}_{it}$, are transformed by subtracting a fraction, $\widehat{\lambda}_i$, of the mean value for each bank from the variables, i.e. $\widetilde{y}_{it} = y_{it} - \frac{\widehat{\lambda}_i}{T_i}\sum_{t=1}^{T_i} y_{it}$ etc. $\widehat{\lambda}_i = 1 - \sqrt{\frac{\widehat{\sigma}_u^2}{\widehat{\sigma}_u^2 + T_i\widehat{\sigma}_c^2}}$. $\widehat{\sigma}_u^2$ is the variance of the error terms in the FE model. $\widehat{\sigma}_v^2$ is the variance in the between model, $\overline{y}_{it} = \overline{\mathbf{x}}_{it}\boldsymbol{\beta} + \overline{u}_{it}$, and $\widehat{\sigma}_c^2 = \widehat{\sigma}_v^2 - \frac{\widehat{\sigma}_u^2}{T}$, see Greene (2008) and Wooldridge (2002).

Hausman test does not reject the RE model simply because the test is not strong enough.

Despite of the caveats, the Hausman test shows that the RE model is preferred in both samples. This allows us to consider bank-specific effects. Furthermore, letting the RE model form the backbone of the estimations is in line with the approach in Uhde and Heimeshoff (2009) and Michalak and Uhde (2009).

Serial correlation

It is assumed that the idiosyncratic errors, v_{it}, are serially uncorrelated both in the RE- and in the FE- model. One of the problems with serial correlation is that the variance matrix estimator is biased. We test for serial correlation by the Wooldridge test, i.e. we test whether $\rho = 0$ in the following regression

$$\ddot{u}_{it} = \rho \ddot{u}_{it-1} + \epsilon_{it}$$

where we regress the error terms from the FE-model on the lagged error terms, see Wooldridge (2002) and Drukker (2003). We find evidence of serial correlation in the sectoral data set for all model specifications, but only for 3 out of 14 model specifications in the data set on industries. The BGT_1-test suggested by Baltagi and Li (1995) for the error component model in equation (5.1) is applied to test for the type of serial correlation, i.e. $H_0 : AR(1)$, $H_1 : MA(1)$. The null hypothesis is rejected in all models where serial correlation is present.

We remove the serial correlation of the MA(1)-type by transformation of the variables in y_{it} and $\mathbf{x}_{it}$ following the approach in Baltagi and Li (1994) and Baltagi (2005, chapter 5.2)[3]. Instead of estimating the moving average parameter, this approach takes the autocovariances of the error term as its starting point. In a first step, the data are transformed recursively such that the transformed dependent variable is given as $y^*_{i1} = y_{i1}$ and $y^*_{it} = \frac{1}{\sqrt{g_t}} \frac{y_{it} - r y^*_{i,t-1}}{\sqrt{g_{t-1}}}$ for $t = 2, ..., T_i$ where $g_1 = 1$ and $g_t = 1 - \frac{r}{g_{t-1}}$ for $t = 2, ..., T_i$ and $r = \frac{E(v_{it} v_{i,t-1})}{E(v_{it} v_{it})}$. The explanatory variables in $\mathbf{x}_{it}$ are transformed in a similar way.

[3] An alternative approach is to estimate the econometric model by GMM. This is a common approach when serial correlation is present, see De Hass and Van Lelyveld (2010) and Akhter and Daly (2009). There are 7 endogenous variables (plus the lagged of the Z-score) to instrument in the sectoral data set, see model 1 in table 5.18. To avoid overfitting of endogenous variables by including too many instruments relative to the number of banks, we collapse the instruments matrix and restrict the number of instruments to two lags per variable we instrument, cf. Roodman (2006, 2008). Despite this, the number of instruments exceeds the number of banks in the sample. The estimation results are not included as there was a serious risk of overfitting the data.

As mentioned in Baltagi (2005), the advantage of this transformation is that it only depends on r, which one can calculate from the autocovariance function of the error term in the original model (5.1) estimated by OLS. In the second step of this approach, we subtract a pseudo average of the variables to ensure that the transformation has zero mean and constant variance, $\sigma^2 I$, where $\sigma^2 = E(v_{it}v_{it})$. Finally, we estimate equation (5.1) using the transformed and serially uncorrelated data.

5.3 The estimated models in the data set on industries

The data set on industries is the most detailed and the lending to the different industries varies between the banks. Therefore, we estimate for effects from the customer composition by industries on the financial soundness of banks here and discuss the results for the sectoral sample in the next section. The following model is estimated

$$\begin{aligned} \text{Z-score}_{it} &= \alpha + \sum_{j=1}^{10} \beta_j LA_{it,j} + \beta_{11}\text{Loan loss provision}_{it} + \beta_{12}\text{Size}_{it} \\ &\quad + \beta_{13}\text{Real GDP growth}_t + \beta_{14}\text{Inflation}_t \\ &\quad + \sum_{h=15}^{22} \beta_h \text{Time dummy}_t + \varepsilon_{it}. \end{aligned} \tag{5.3}$$

Customer composition is measured by the loans to assets, LA, for the most important industries, see table 5.3. As already mentioned, the expected signs of the customer composition are indeterminate. According to the descriptive statistics there are banks that do not lend out to *Financial leasing* and *Investment funds*, see table 5.5.

We include loan loss provision and bank size measured by the natural logarithm of assets in equation (5.3) to capture bank-specific characteristics. The overall economic activity is measured by real GDP growth and inflation. Time dummies are included to account for effects that are common to all banks, but not captured by the customer composition, bank-specific and macroeconomic variables.

5.3.1 Main results and changes in bank-specifics and business cycle

Model 1 in table 5.7 shows the results for equation (5.3). The size of the banks, the real GDP growth and the loans to assets for *Building and construction* and *Sale of motor vehicles and automotive fuel* come out significantly.

The reason for the positive impact from these industries on the Z-score of the banks might be that both industries are rather sensitive to the business cycle and the state of the business cycle impacts the Z-score. As expected, the financial soundness tends to decrease the larger a bank is and increase with the state of the business cycle. Note also that the coefficient of the loan loss provision is rather large because the value of this variable is low.

More variables become significant when we exclude time dummies in model 2, e.g. loans to assets for *Farming, Investments funds, Building and construction* and *Sale of motor vehicles and automotive fuel* are significant. All bank-specific and macroeconomic variables are also significant. The lending to the same four industries and the real GDP growth are significant when we exclude the bank-specific variables in model 3. That is, the results from the preferred model are confirmed by and large when excluding the time dummies or the bank specific variables.

We include more bank-specific variables, large exposures, cost-income ratio and growth in loans, in model 4. Neither of these additional bank-specific variables is significant and they do not contribute much to R^2 so it seems fair to include only loan loss provision and bank size in the preferred model. However, the lending to assets for *Investment funds* affects the Z-score now.

Although we exclude the business cycle variables in model 5, we find almost the same results as in the preferred model (model 1). This suggests that the time dummies proxy the overall macroeconomic development quite well.

To sum up, the results are relatively robust towards exclusion of time dummies (model 2), changes in the bank-specific variables (model 3-4) and exclusion of macroeconomic variables (model 5).

5.3.2 Sensitivity with respect to customer composition

Model 6-9 consider the robustness with respect to the customer composition. The results are shown in table 5.8.

The customer composition for industries is excluded in model 6. This implies only a small decrease in R^2, e.g. the customer composition explains only a relatively small part of the total variation in the Z-score. This is surprising since the banks lending activities play a major role in the banks' accounts.

Until now, the customer composition has been measured by the loans to assets for the selected industries. We replace it by the deposit surplus to assets as a robustness check in model 7. That is, for each of the industries, we calculate the deposit surplus, deposits minus lending, to assets for the selected industries. Even though the banks lend a lot to a specific industry, the deposits from this industry can offset the lending. Thus, lending to a specific industry is not necessarily critical for the financial soundness of banks. This is the argument for considering the deposit surplus. The expected signs of the customer composition in industries are still unknown with this alternative measure.

The results for model 7 show that the deposit surplus for *Sale of motor vehicles and automotive fuel*, bank size and one of our business cycle indicators affect the financial soundness of the banks significantly. Thus, compared with the preferred model (model 1) lending to *Building and construction* has no impact on the Z-score. Moreover, the impact of *Sale of motor vehicles and automotive fuel* on the Z-score is positive when we measure it by loans to assets, but negative measured by the deposit surplus to assets. Thus, the measure of customer composition matter for the results.

To check how sensitive the results are towards the selection of the most important industries, we apply a second selection criterion. The most important industries are now those with the highest loans to assets ratio on average. The reason for this is that the banks can control their lending, but not the deposits, directly. That is, by considering the most important industries selected by the loans to assets ratio we identify the industries to which the banks have chosen to expose themselves. The selection of the most important industries is relatively stable since 6 of the selected industries are the same as before, see table 5.3. *Employees, Banks* and *Business activities* are new important industries with the changed selection criterion.

The customer composition in model 8 is based on the alternative selection criterion for the most important industries. We measure it deposit surplus to assets. The results show that only banks' size and the business cycle indicators affect the financial soundness of the banks.

This conclusion is largely the same in model 9, where the customer composition is measured by the loans to assets for the alternative selection criterion. The main difference between model 8 and 9 is that lending to *Business activities* is significant in model 9.

Overall, the results in model 7-9 are not robust neither with respect to the measure of customer composition (loans or deposit surplus to assets) nor with respect to the selection criterion for the most important industries. However, the size of the banks and the business cycle affects the Z-score significantly in all these models. Thus, what really matters for the financial soundness of banks are their size and business cycle effects, whereas the effects of the customer composition are surprisingly small.

5.3.3 Z-score components and the solvency ratio

This section considers the relation between the components of the Z-score and the preferred set of regressors. There are two reasons for this. First, a better understanding of the relationship between the Z-score and the explanatory variables can be gained from analyzing how the underlying Z-score components depend on the preferred set of regressors. That is, we would like to figure out which of the components that drive the overall results for the Z-score in the preferred model. This approach is common in the literature on banks' Z-scores, see Uhde and Heimeshoff (2009), Fungáčová and Solanko (2008) and Michalak and Uhde (2009). Table 5.4 present the correlations between the Z-score and its components, the return on average assets (ROAA), the capital ratio and the volatility of the ROAA (sdROAA). The correlations are strongest between Z-score and ROAA and between Z-score and capital ratio.

Second, as we discussed above, the Z-score measure might not reflect the actual financial soundness of a bank properly if the bank is large or has stable returns over time. Thus, the components of the Z-score might be better measures of banks' financial soundness. Akhter and Daly (2009) analyze banks' financial soundness using the return on assets, the capital ratio and the solvency ratio as different measures of banks' financial soundness. They argue that the capital ratio and the solvency ratio are two different measures of the capital adequacy. This is confirmed by the correlation between the capital ratio and the solvency ratio, see table 5.4.

The summary statistics of the Z-score components and the solvency ratio are shown in table 5.5. As expected, the summary statistics of the capital ratio and the solvency ratio reflect that the solvency ratio must be at least 8 per cent by law and that the two measures are alike. The return on average assets, ROAA, might seem low compared with the capital ratio. However, Boyd et al. (2006) find the same in a sample of US banks. The mean values of the return on average assets, return volatility and capital ratio in the data set on industries are in line with the mean values in the US sample. The reason for the low value of ROAA compared with the capital ratio might be sample selection. That is, ROAA is smaller than the capital ratio in our samples and the US sample, but this reverses in the sample used by Uhde and Heimeshoff (2009).

Thus, we regress the three components of the Z-score and the solvency ratio of the preferred set of explanatory variables. The results are shown in model 10-13 in table 5.9.

In model 10, the banks' profitability is affected by the loans to assets ratio for *Farming*, *Investment funds*, *Other financial service activities* and *Building and construction*. As we would expect from our findings so far, the real GDP growth has a significant and positive influence on the profitability. Somehow surprising, the bank size does not affect the variation in the return on average assets significantly.

We regress the capital ratio on the preferred set of regressors in model 11 and find that lending to *Sale of motor vehicles and automotive fuel*, bank size and real GDP growth have significant impact on the capital ratio.

The other proxy of capital adequacy of banks, the solvency ratio, is regressed on the preferred set of explanatory variables in model 12. The customer composition with respect to *Real estate activities and renting*, *Investment funds* and *Wholesale except motor vehicles* plus the state of the business cycle are significant. Somewhat surprisingly, the real GDP growth affects the solvency ratio negatively such that the solvency of banks decreases during economic booms. A possible reason for the differences between model 11 and 12 is that the denominator in the solvency ratio consists of risk-weighted assets, whereas the assets in the denominator of the capital ratio are unweighted.

Finally, the volatility of the banks' returns replaces the Z-score as the dependent variable in model 13. Note that we exclude time dummies in this model. The reason for this is that there is perfect positive autocorrelation, AR(1), if we include time dummies in model 13, but no serial correlation if we exclude them.

The following variables affect the volatility of returns significantly, lending to *Real estate activities and renting, Investment funds*, *Other financial service activities*, *Building and construction* and *Other industries* plus bank size, real GDP growth and the inflation rate. Lending to *Real estate activities and renting* and *Investment funds* have been mentioned in relation to critical exposures in the banks during the financial crisis.

It makes sense that the volatility of the returns increases with loan loss provision and bank size and decreases with the business cycle. Banks with large loan loss provisions might have returns that are more volatile since a bank cannot know whether the customers are able to serve their loans. Moreover, during economic booms, all banks have more stable returns and this decreases the volatility of the returns.

Furthermore, larger banks have returns that are more volatile. The reason for this might be that larger banks can engage in lending to larger investment projects. That is, even though the risk of a specific investment project is modest, the potential losses can be substantial because of the size of the engagement. Moreover, larger engagements might imply a more concentrated loan portfolio. This is expected to affect the financial soundness of banks negatively as we discussed above.

Thus, the results for the Z-score components and the solvency ratio in model 10-13 show that the banks exposure towards other industries than *Building and construction* and *Sale of motor vehicles and automotive fuel* matter. Moreover, the results for the preferred model for the Z-score seem to the driven mostly by two of the Z-score components, the capital ratio and the profitability of banks. At least one of these variables is affected by the business cycle, bank size and lending to *Building and construction* and *Sale of motor vehicles and automotive fuel*.

5.4 The estimated models in the sectoral data set

The sectoral sample is considered here as a robustness check of the results in the data set on industries. An advantage in this sample is that we have access to more observations since all banks report data on their lending and deposits for the sectors during the sample period.

Originally, 56 banks were included in the sectoral sample. In addition to the 22 banks in the current sectoral sample, 34 small banks were included. These 56 banks account for 87.4 per cent of the total assets on average during the sample period, where the 22 banks in the current sample account for 84.3 percent as mentioned above. Thus, adding 34 banks more only increases the market share of the sample-banks a little.

Two problems emerge in the enlarged sample. First, the earnings over time for the smallest banks are relatively stable. This implies that there are only minimal changes in these banks' Z-scores. Boyd et al. (2006) mentioned this situation and the enlarged sectoral sample confirms this. Second, the Hausman F-test is indecisive in the enlarged sectoral sample. Thus, it seems as if there is not enough variation in the explanatory variables over the sample period to determine if the FE or RE model is preferred, see

Greene (2008). This adds to the discussion of the use of the Hausman test statistic in section 5.2. For these reasons, the current sectoral sample includes data for 22 large and medium-sized banks. As already noted and shown in the tables below, the Hausman test statistic is decisive in favor of the RE model in the sectoral sample consisting of 22 banks.

Although there are more observations in the sectoral sample than in the data set on industries, the division into sectors is more aggregated than the customer composition in industries. This implies that it becomes harder to find an impact of the customer composition on the financial soundness in the sectoral sample.

The degree of serial correlation is another disadvantage in this sample. There is serial correlation for all model specifications in the sectoral data set, but only for three of the model specifications in the data set on industries. The preferred models for these samples, shown in equation (5.3) and (5.4), are almost equal. This suggests that the serial correlation might not be due to omitted variable bias. Another possibility is inertia in the data or delayed effects such that Z-score is affected by lagged values of the explanatory variables. If this were the case, we would expect to find serial correlation in all model specifications in the industrial sample too.

A completely different, but conceivable explanation is the statistical definitions underlying the sectoral decomposition of customers. First, *MFIs* and *Firms* cover a wide range of different - financial respectively non-financial - economic activities, see table 5.16. Some of these activities affect the financial soundness of banks positively and others have a negative effect. This might imply that the overall effects from lending to these sectors on the Z-score become blurred. Second, the banks might lend almost the same amount to each of the sectors over time. Both effects could cause the serial correlation in the sectoral sample.

Despite of these caveats, we estimate the following model to see if we can confirm the impact of the customer composition on the financial soundness of banks in the sectoral sample

$$\begin{aligned} \text{Z-score}_{it} = {} & \alpha + \sum_{k=1}^{4} \beta_k LA_{it,k} + \beta_5 \text{Loan loss provision}_{it} + \beta_6 \text{Size}_{it} \\ & + \beta_7 \text{Cost-income ratio}_{\text{it}} + \beta_8 \text{Real GDP growth}_t + \beta_9 \text{Inflation}_t \\ & + \sum_{h=10}^{17} \beta_h \text{Time dummy}_t + \varepsilon_{it}. \end{aligned} \tag{5.4}$$

Note that all variables have been transformed to correct for the serial correlation in the data set, see section 5.2 for more on this.

The loans to assets, LA, for the four sectors measure the customer composition. *Households* and *Firms* make up most of the banks' customers, see table 5.15. Moreover, note that some banks do not engage in lending to the *Government* sector just as there are banks, which do not lend to *Households*, see table 5.15.

There are three bank-specific variables, loan loss provision, bank size measured by the share of assets and the cost-income ratio.

The natural logarithm of assets is a common measure of bank size; see Fungáčová and Solanko (2008) and Boyd et al. (2009). This common measure of bank size was included in the estimation on the data set on industries. However, bank size is measured relatively by bank i's share of assets in the estimations on the sectoral sample[4]. This is the best available[5] proxy for bank size as the natural logarithm of assets is highly correlated with the loans to assets for *Households* and *MFIs*, see table 5.21. The relative size measure is only correlated with lending to *MFIs.*

The cost-income ratio is included since it is significant in some of the model specifications in the sectoral data set. Remember that this variable was insignificant and therefore not included in the preferred model in the data set on industries, see model 4 in table 5.7.

Finally, we include the same macroeconomic variables and time dummies as in equation (5.3).

5.4.1 Main findings and sensitivity towards changed regressors

The results for the preferred model are in model 1 in table 5.18. This model explains about the same fraction of the total variation in the Z-score as the preferred model does

[4]The effects of measuring bank size by share of assets have also been considered in the data set on industries. Most of the results are unchanged compared with the preferred model. The real GDP growth and the loans to assets for *Building and construction* and *Sale of motor vehicles and automotive fuel* affect the financial soundness of banks. However, in opposition to the preferred model for the data set on industries, the banks' financial soundness is affected by lending to *Investment funds* and loan loss provisions, but bank size in insignificant.

[5]The banks' share of total loans and their share of total returns have also been considered as alternative measures of bank size. Moreover, different transformations, $log(x)$, $exp(x)$, $\frac{1}{x}$, x^2 etc. of assets, the natural logarithm of the assets and of banks' share of assets have been tried out. Both the alternative size measures and the different transformations of the size measures are correlated with the loans to assets ratio for at least one of the sectors.

in the data set on industries, see model 1 in table 5.7. The lending to *Households* is significant as well as the size of banks and the macroeconomic variables in model 1. The significant influence of the inflation rate is in contrast to the results for the data set on industries.

The most pronounced effects from excluding the time dummies in model 2 are the halving of R^2 and that the FE-model is preferred to the RE-model. The decrease in R^2 was smaller in model 2 in the data set on industries. Model 2 is the only one where the FE-model is preferred in the sectoral data set. Therefore, we show results both from the RE- and the FE-model and the significant variables are the same here. The lending to *Households* and *Firms*, the loan loss provisions, the cost-income ratio and the inflation rate are significant. However, the size of banks is no longer significant. This might be due to the relative measure of bank size.

The bank-specific variables are changed or excluded in model 3-5. Lending to *Households* and the business cycle effects are significant in model 3 and an additional variable, the bank size, is significant in model 4. The same four variables are significant when we replace the measure of bank size by the natural logarithm of assets in model 5. Thus, the results are relatively robust towards changes in the bank-specific variables.

The lending to *Households* and the size of the banks are the only significant variables in model 6, where the business cycle indicators are excluded. The R^2 is almost unchanged so the time dummies seem to capture the state of the business cycle quite well. This is in line with the findings in the data set on industries.

When we exclude the customer composition in model 7, there is a rather substantial drop in the R^2. This contrasts the results for the data set on industries, see the results for model 6 in table 5.8. Thus, the customer composition in sectors matter for the banks' Z-scores. The loan loss provisions, bank size and the business cycle indicators affect the Z-score.

As a robustness check we proxy the customer composition by deposit surplus to assets for each sector. The expected signs of the deposit surplus to assets for the specific sectors are unknown. An advantage from changing the measure of the customer composition in sectors is that the correlation between deposit surplus to assets for the four sectors and the bank size is rather low, see table 5.22. The results in model 8 show that all regressors except from the loans to assets for the *Government* and the cost-income ratio are significant. Note that the signs of the deposit surplus to assets for *Households* and *MFIs* are opposite of the signs for loans to assets for the corresponding sectors in model 1. Thus, it matters for the results whether we consider the deposits or not.

Overall, the results for the sectoral sample confirm the results for the data set on industries. It is surprising though that the industries that matter for the financial soundness of banks do not correspond to the sectors, which have significant influence. Thus, we expect to find an impact from lending to *Firms* in the sectoral sample since the industries *Building and Construction* and *Sale of motor vehicles and automotive fuel* belong to this sector. Moreover, the significant impact of lending to the *Households* sector is unexpected, as lending to *Employees* did not influence the financial soundness in the data set on industries.

5.4.2 Z-score components and the solvency ratio

In line with the approach for the data set on industries, we regress each of the Z-score components and the solvency ratio on the preferred set of explanatory variables from model 1. As we discussed previously, the idea is to obtain a better understanding of relationship between the customer composition for the sectors and the banks' profitability, their capital ratio and how volatile their returns are and to overcome the critique that the Z-score measure might not respond to a changed risk scheme for all banks.

The correlations between the Z-score, its components and the solvency ratio shown in table 5.17 do not differ that much from those in table 5.4.

The results for the estimated models are shown in table 5.20. The return on average assets, ROAA, is regressed on the preferred set of explanatory variables in model 9. We find that the loans to assets for the *Government*, the cost-income ratio and the macroeconomic variables affect the banks profitability significantly.

When we replace the Z-score by the banks' capital ratio in model 10, we find results in line with model 1 as lending to *Households*, bank size and business cycle variables come out significantly.

The results change for the other proxy for the capital adequacy of banks, the solvency ratio. All sectors, except *Households*, plus the bank size, cost-income ratio and real GDP growth have significant impact on the solvency ratio. The negative impact of the lending to *Firms* might be because lending to *Firms* is more risky than lending other sectors since some enterprises might have an uncertain return profile on their investments. The positive impact of bank size and the cost-income ratio on the solvency ratio show that larger or more effectively driven banks are more financially stable than other banks. In the data set on industries, we did not find an effect of bank size on the solvency ratio. In contrast to this, there was also a negative contribution of the real GDP growth in the data set on industries. To sum up, the results for the two measures of capital adequacy differ. This confirms the results for the data set on industries.

The approach with respect to return volatility (sdROAA) is the same as for the other sample. That is, we find perfect positive autocorrelation, AR(1), if we include time dummies in model 12. Without time dummies we find serial correlation to a lesser extent of the MA(1)-type. Thus, model 12 is estimated without time dummies.

The customer composition for the sectors does not affect the volatility of the banks' returns. On the contrary, loan loss provisions, the cost-income ratio and the business cycle indicators have significant impact in model 12. The positive impact of the loan loss provision was also found in the data set on industries and the underlying reasons are the same. Moreover, the positive impact of the cost-income ratio means that more efficiently driven banks have returns that are more volatile. This is not that intuitive, but the contribution to the return volatility is modest compared with the other significant variables.

To sum up, the lending to three out of four sectors matter for the solvency ratio. Lending to *Households* (*Government*) has significant impact on the capital ratio (profitability of banks). Furthermore, the results for the capital ratio seem to be closest to the results for the preferred model for the Z-score (model 1) in the sense that the same variables come out significantly.

5.5 Conclusion

This paper considers the relationship between the banks' financial soundness and the composition of their customers. The customer composition are either divided into 50 different industries (*Real estate activities and renting*, *Farming*, *Building and construction, Wholesale except motor vehicles* etc.) or 4 different sectors (*Households*, *Firms*, *Government* and *Monetary and financial institutions, MFIs*). To my knowledge, this is the first paper that analyzes the relationship between the banks' financial soundness and their lending to specific industries and sectors.

We have access to unique micro-level data for each bank's lending and deposits subdivided into industries and sectors during the period 2000-2008. Bank-specific variables and macroeconomic indicators are also included among the explanatory variables. The financial soundness of banks is measured by the Z-score technique.

The first set of results is based on the data set on industries since this has the most detailed customer composition. We find that the lending to *Building and construction* and *Sale of motor vehicles and automotive fuel* matter for the financial soundness of banks. However, the impact of customer composition for the industry dimension is surprisingly small. What really matters is business cycle effects and the bank size. Thus, banks are less financially stable during recessions or if they are large. The significant effects from bank size and macroeconomic indicators on banks' financial soundness are also confirmed by Akhter and Daly (2009) and Fungáčová and Solanko (2008).

The results are relatively stable towards changes in the bank-specific variables or the macroeconomic indicators. However, the results are sensitive towards changes in the measure of customer composition, i.e. replacing lending to assets by deposit surplus to assets changes the results. Furthermore, even though 6 of the selected industries are the same, the results change if we select the most important industries by an alternative selection criterion.

These findings are confirmed by the estimations on the sectoral sample. Somewhat surprising, we find that the lending to *Households* affect the financial soundness of banks significantly along with the macroeconomic indicators and the size of the banks. We expect that the industries that matter for the financial soundness of banks correspond to the sectors, which have significant influence. That is, we expect to find an impact from lending to *Firms* in the sectoral sample since the industries *Building and Construction* and *Sale of motor vehicles and automotive fuel* belong to this sector. Moreover, the significant impact of lending to the *Households* sector is unexpected as lending to *Employees* did not influence the financial soundness in the data set on industries.

The Z-score combines three different indicators for bank health in one number. We consider the Z-score components for two reasons. First, we gain a deeper understanding of which of the components that drive the overall results for the Z-score. Second, we check the robustness of the measure of financial soundness. As touched upon above, the Z-score technique might blur the effects of the customer composition since banks with a stable return over time tends to have high Z-scores and large banks tend to have smaller Z-scores than other banks. Thus, we regress the Z-score components, profitability of banks, capital ratios and the volatility of returns, on the preferred set of explanatory variables. As a further robustness check of the capital ratio, we also regress the solvency ratio on the preferred set of regressors.

More industries (*Farming*, *Investment funds*, *Other financial service activities*, *Real estate activities and renting*, *Wholesale except motor vehicles* and *Other industries*) and sectors (*MFIs*, *Firms*, *Government*) come out significantly when we consider the components of the Z-score and the solvency ratio. Furthermore, in the data set on industries, the results for the preferred model for the Z-score seem to the driven mostly by two of the Z-score components, the capital ratio and the profitability of banks. The capital ratio drives the results for the Z-score in the sectoral sample.

Another advantage of the Z-score technique is that one can calculate it - relatively simple and for all banks - from publicly available accounts. More advanced models of the probability of bank default might be difficult to understand for the regular bank customer. This could for instance be due to required detailed data, which are available to the financial authorities only. Furthermore, it is quite difficult to determine the timing of a bank failure for sure. That is, a bank can achieve extra attention from the financial authorities before announcing that a bank has become financially unstable. Moreover, financial authorities might prevent bank defaults of systemic important banks to prevent contagion effects and a systemic crisis in the national banking sector. The ongoing development of new - national and international - regulation or improved analytical tools might also imply that financial authorities react differently to bank failures during time. The Z-score technique can overcome some of these difficulties, so despite of its caveats, the Z-score is a useful tool for analyzing the financial soundness of banks.

To sum up, although the empirical evidence could be stronger, the results support the Basel Committee's view on the need to keep track of the banks' exposure towards certain groups of customers, including industries or economic sectors. An interesting extension of the analysis in this paper is to analyze whether the influence of certain sectors or industries on banks' Z-scores, or the Z-score components, become stronger in a cross-country sample or if specific industries or sectors affect banks' financial soundness in a restricted geographical area.

5.6 References

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5.7 Appendix: Tables

Table 5.1: Commercial banks and savings banks in the data sets

Group	Reg. No.	Name	Annual accounts	N(sectors)	N(industries)
1	2222	Nordea Bank Danmark A/S	2000-2008	9	9
1	3000	Danske Bank A/S	2000-2008	9	9
1	7858	Jyske Bank A/S	2000-2008	9	9
1	8079	Sydbank A/S	2000-2008	9	9
1	8117	Nykredit Bank A/S	2000-2008	9	9
1	10001	FIH Erhvervsbank A/S	2000-2008	9	6
2	0522	Sjælland, Sparekassen	2000-2008	9	2
2	0725	Fionia Bank A/S	2000-2008	9	9
2	5201	Amagerbanken Aktieselskab	2000-2008	9	9
2	5301	Arbejdernes Landsbank, Aktieselskab	2000-2008	9	9
2	5470	Forstædernes Bank A/S	2000-2008	9	9
2	6160	Roskilde Bank, Aktieselskab	2000-2007	8	8
2	7670	Ringkjøbing Landbobank, Aktieselskab	2000-2008	9	7
2	7681	Alm. Brand Bank A/S	2000-2008	9	9
2	7730	Vestjysk Bank A/S	2000-2008	9	6
2	9260	Sparbank A/S	2000-2008	9	9
2	9380	Spar Nord Bank A/S	2000-2008	9	9
3	0400	Lån og Spar Bank A/S	2000-2008	9	9
3	7440	Nørresundby Bank A/S	2000-2008	9	6
3	7650	Ringkjøbing Bank, Aktieselskabet	2000-2007	8	1
3	9217	Himmerland A/S, Sparekassen	2000-2008	9	2
3	9335	Kronjylland, Sparekassen	2000-2008	9	9
Total		22 banks		196	164

Note: N(sectors) (N(industries)) is the number of observations in the sectoral data set (data set on industries). There are fewer observations in the data set on industries than in the sectoral data set, since all banks report the sectoral data to the statistics on banks lending and deposits, whereas the customer composition for industries is available for banks, which report in full to the statistics. The Danish Financial Authorities (FSA) group banks by their productively employed capital (PEC) comprised by deposits, issued bonds, subordinated debt and equity capital. Group 1: Banks with PEC above 50 billion DKK, group 2 (3) banks with PEC between 10 and 50 billion DKK (between 250 million DKK and 10 billion DKK). The grouping of banks in 2009 is used. The latest known grouping is used for banks involved in mergers or take-overs during the estimation period.

Table 5.2: Variables and data sources

Variable	Description	Data sources
Z-score	(ROAA-Capital ratio)/sdROAA	Accounting data, own calc.
ROAA	Return on average assets before taxes	Accounting data, own calc.
sdROAA	Standard deviation of ROAA	Accounting data, own calc.
Capital ratio	Ratio of equity capital to total assets	Accounting data, own calc.
Solvency ratio, per cent	Regulatory capital as share of risk-weighted assets, at least 8 per cent by law	Accounting data
Ratio of lending to total assets, LA	Ratio of lending to assets for sector k resp. industry j	Danmarks Nationalbank, own calc.
Ratio of deposit surplus to total assets, DSA	Ratio of deposit surplus to assets for sector k resp. industry j	Danmarks Nationalbank, own calc.
Loan loss provisions to total assets	Loan loss provisions to total assets	Accounting data, Danmarks Nationalbank, own calc.
Size, $log(assets_i)$	The natural logarithm to bank i's assets, $log(assets_i)$	Danmarks Nationalbank, own calc.
Size, bank i's share of total assets	Ratio of bank i's assets to total assets	Danmarks Nationalbank, own calc.
Growth in loans, per cent	$(\text{loans}_{t+1} - \text{loans}_t)/\text{loans}_t$. Zero in the period after a merger	Accounting data, own calc.
Cost-income ratio	Ratio of total costs to total revenue	Accounting data, own calc.
Large exposures	Sum of large exposures to total assets	Accounting data, Danmarks Nationalbank, own calc.
Real GDP growth, annual growth rate	Growth in seasonally adjusted GDP in 2000 prices	Statistics Denmark, own calc.
Inflation, annual growth rate	Growth in HICP	Statistics Denmark, own calc.

Note: Total assets is made up either from the assets or the liabilities side. Made up from the assets side, total assets consist of Cash, Loans, Securities other than shares, Money market funds shares, Shares and other equity, Financial derivatives and Remaining assets. Based on liabilities, the total assets are equal to the sum of Currency in circulation, Deposits, Money market funds shares, Debt securities issued, Capital and reserves, Financial derivatives and Remaining liabilities. Accounting data are from banks' accounts. Data on the banks' lending, deposits and total assets are from Danmarks Nationalbank.

Table 5.3: Most important industries

No.	**Based on deposit surplus to total assets**	**Based on lending to total assets**
1	Real estate activities and renting	Employees etc.
2	Financial leasing	Real estate activities and renting
3	Farming	Banks
4	Investment funds	Farming
5	Other financial service activities	Business activities
6	Wholesale except motor vehicles	Financial leasing
7	Building and construction	Building and construction
8	Mfr. of metals and metal products	Wholesale except motor vehicles
9	Sale of motor vehicles and automotive fuel	Other financial service activities
10	Other industries	Other industries

Note: The most important industries are selected based on the deposit surplus to assets (DSA) in the upper part of the table and the selected industries are sorted such that the industry with the lowest deposit surplus to assets is number 1 and so forth. In the lower part of the table, the most important industries are selected based on the loans to assets (LA). The industry with the highest loans to assets ratio is number 1 and so forth. Note that 6 of the selected industries are identical. Other industries include industries different from the 9 most important. Financial leasing are for assets where the term approx. covers the expected life of the asset. The lessee acquires substantially all the benefits of its use and takes all the risks associated with its ownership. Other financial service activities include writing of swaps, options and other hedging arrangements etc. Business activities include computer equipment and services, research and development, legal, accounting, architectural and engineering activities, advertising etc.

Table 5.4: Correlations between Z-score, Z-score components and solvency, data set on industries

	Z-score	ROAA	Capital ratio	sdROAA	Solvency
Z-score	1.00				
ROAA	0.64	1.00			
Capital ratio	0.86	0.45	1.00		
sdROAA	-0.47	-0.42	-0.02	1.00	
Solvency	0.40	0.19	0.60	0.23	1.00

Table 5.5: Summary statistics, data set on industries

Variable	N	Mean	Median	Min	Max	Std
Z-score	164	10.8870	9.5920	0.0333	33.2922	5.6554
ROAA, per cent	164	1.2086	1.1546	-4.6998	4.2271	1.1421
sdROAA, per cent	164	0.9359	0.8681	0.6816	1.5578	0.2663
Capital ratio, per cent	164	8.2721	7.1692	3.0091	19.9819	3.8264
Solvency, per cent	164	12.2421	11.8000	8.3000	23.0000	2.2325
Customer composition						
LA, Real estate activities and renting	164	6.7819	5.9402	0.1115	28.3612	5.1878
LA, Financial leasing	164	2.1511	0.6110	0.0000	13.8684	2.9256
LA, Farming	164	3.1161	2.4943	0.0752	14.5123	3.1332
LA, Investment funds	164	1.6237	0.3857	0.0000	16.4249	2.7043
LA, Other financial service activities	164	1.8100	0.8716	0.0006	21.3397	3.3404
LA, Wholesale except motor vehicles	164	2.0128	2.1343	0.0616	5.7131	1.2181
LA, Building and construction	164	2.0121	1.5001	0.0610	10.9861	2.0245
LA, Mfr of metals and metal products	164	1.0811	0.8957	0.0176	8.9425	1.1341
LA, Sale of motor vehicles etc.	164	0.8934	0.8706	0.0041	3.0655	0.6196
LA, Other industries	164	37.6640	37.5035	17.4293	68.7224	11.1357
LA, All industries	164	59.1460	60.8023	21.1773	106.2652	15.3928
Bank characteristics						
Loan loss provision to assets	71	0.0007	0.0005	0.0000	0.0054	0.0008
Growth in loans, per cent	159	6.7651	6.2022	-12.1879	35.0565	8.8019
Size, log(assets)	164	10.3813	9.8985	8.4044	14.6208	1.4506
Cost-income ratio	164	3.7225	1.8221	-35.5415	272.6656	21.5942
Large exposures to assets	131	0.0064	0.0044	0.0000	0.0336	0.0068
Macroeconomic variables						
Real GDP growth, y-y	9	1.2001	2.0587	-3.7570	2.7512	2.1324
Inflation, y-y	9	1.9994	2.2358	0.9231	2.5559	0.5788

Note: LA is lending to total assets. y-y means annual growth rates. The most important industries is selected based on the average of deposit surplus to total assets for all banks in the sample. In general, the names of the industries have been abbreviated, see table (5.14). Growth in loans is set to zero 5 times where the growth rate jumps up due to merger activity. Loan loss provisions and large exposures to assets are only reported by banks when relevant. The minimum values for loan loss provision and large exposures are very small, but different from zero. The Z-score components, ROAA, sdROAA and capital ratio, are measured in per cent.

Table 5.6: Correlations between explanatory variables, data set on industries

	LA, Real estate	LA, Fin. leasing	LA, Far-ming	LA, Inv. funds	LA, OFSA	LA, Whole-sale	LA, Bldg-constr	LA, Mfr of metals
LA, Real estate	1.00							
LA, Fin. leasing	0.03	1.00						
LA, Farming	0.03	-0.16	1.00					
LA, Inv. funds	0.35	0.28	0.09	1.00				
LA, OFSA	0.00	0.11	-0.10	0.36	1.00			
LA, Wholesale	0.21	-0.09	0.48	-0.21	-0.38	1.00		
LA, Bldg-constr	0.64	0.08	0.18	0.20	-0.17	0.22	1.00	
LA, Mfr of metals	0.24	-0.17	0.17	-0.20	-0.26	0.65	0.08	1.00
LA, SMV	0.20	-0.18	0.33	-0.28	-0.28	0.59	0.36	0.32
LA, Other indu.	0.06	-0.42	0.36	-0.22	-0.31	0.30	0.20	0.20
Loan loss	0.07	0.01	0.06	-0.13	-0.07	-0.08	0.09	-0.09
Size	-0.25	0.14	-0.28	-0.08	-0.11	-0.06	-0.31	0.03
Growth in loans	0.23	0.04	0.11	0.22	-0.02	0.10	0.36	-0.13
Large exposures	0.27	0.11	-0.17	0.27	0.44	-0.24	0.20	-0.19
Cost-income ratio	-0.11	-0.05	-0.06	-0.06	0.01	-0.11	-0.07	-0.08
Real GDP growth	-0.03	0.03	-0.06	-0.01	0.02	0.05	0.05	0.05
Inflation	-0.02	-0.05	-0.03	0.04	0.07	-0.09	0.03	-0.17

	LA, SMV	LA, Other indu.	Loan loss	Size	Growth in loans	Large expo-sures	Cost-income ratio	Real GDP growth	Infla-tion
LA, Real estate									
LA, Fin. leasing									
LA, Farming									
LA, Inv. funds									
LA, OFSA									
LA, Wholesale									
LA, Bldg-constr									
LA, Mfr of metals									
LA, SMV	1.00								
LA, Other indu.	0.49	1.00							
Loan loss	0.21	0.11	1.00						
Size	-0.42	-0.64	-0.15	1.00					
Growth in loans	0.17	0.20	-0.10	-0.18	1.00				
Large exposures	-0.06	0.06	-0.05	-0.57	0.10	1.00			
Cost-income ratio	-0.09	0.25	-0.04	-0.12	-0.06	0.03	1.00		
Real GDP growth	0.02	-0.04	-0.20	-0.05	0.37	0.07	-0.17	1.00	
Inflation	-0.03	0.08	0.01	0.02	0.01	-0.08	0.06	-0.34	1.00

Note: LA is lending to assets. Real estate is real estate activities and renting, Fin. leasing is financial leasing, Inv. funds is investment funds, OFSA is other financial service activities, Wholesale is wholesale except motor vehicles, Bldg-constr is building and construction, Mfr of metals is Mfr of metals and metal products, SMV is sale of motor vehicles and automotive fuel and Other indu. is other industries. Loan loss (Large exposures) is loan loss provisions (large exposures) to assets. Size is the natural logarithm to assets.

Table 5.7: Z-score and customer composition for industries, preferred model and sensitivity wrt. bank characteristics

	(1) RE Z-score	(2) RE Z-score	(3) RE Z-score	(4) RE Z-score
LA, Real estate	-0.0147	0.0110	-0.0077	-0.0192
	(0.0661)	(0.0502)	(0.0673)	(0.0671)
LA, Financial leasing	-0.0766	-0.0479	-0.1133	-0.0898
	(0.0806)	(0.0934)	(0.0899)	(0.0818)
LA, Farming	0.3106	0.3756**	0.4199*	0.3299
	(0.2446)	(0.1837)	(0.2502)	(0.2360)
LA, Investment funds	-0.2040	-0.3043**	-0.2238*	-0.2178*
	(0.1262)	(0.1258)	(0.1332)	(0.1263)
LA, Other fin. service	-0.0100	-0.0102	0.0019	-0.0236
	(0.0761)	(0.0576)	(0.0830)	(0.0792)
LA, Wholesale	-0.2736	-0.2814	-0.2894	-0.3222
	(0.7178)	(0.7106)	(0.7400)	(0.7429)
LA, Building and construction	0.3601**	0.5164***	0.4017**	0.3493**
	(0.1555)	(0.1917)	(0.1713)	(0.1592)
LA, Mfr of metals	-0.1818	-0.2902	-0.3855	-0.1126
	(0.4127)	(0.3981)	(0.4119)	(0.4458)
LA, Sale of motor vehicles	1.5700**	1.6759**	2.2562***	1.4858**
	(0.6642)	(0.8384)	(0.6403)	(0.6550)
LA, Other industries	-0.0006	0.0099	0.0417	-0.0116
	(0.0335)	(0.0205)	(0.0321)	(0.0375)
Loan loss provision	-526.4039	-1320.4633***		-448.5817
	(340.3624)	(277.1547)		(343.2671)
Size, log(assets)	-1.9798***	-1.4873***		-2.0428***
	(0.6364)	(3.0000)		(0.6280)
Large exposures				-22.2782
				(30.6111)
Cost income ratio				0.0029
				(0.0045)
Growth in loans				0.0146
				(0.0286)
Real GDP growth	1.4679***	1.1376***	1.5554***	1.4642***
	(0.1304)	(0.1154)	(0.1430)	(0.1458)
Inflation	0.7955	1.2277***	-0.1115	0.7790
	(0.6379)	(0.2672)	(0.5844)	(0.6508)
Constant	41.5935***	30.6278***	6.2284***	43.2773***
	(11.7951)	(5.8474)	(2.3414)	(11.8415)
Time dummies	Yes	No	Yes	Yes
No of obs	164	164	164	164
No of banks	22	22	22	22
Wooldridge test for serial correlation	0.88	9.76***	0.25	1.07
BGT_1-test, H_0: AR(1), H_1: MA(1)		-0.37***		
Wald-test for overall fit	364.28***	280.05***	359.36***	501.16***
Hausman F-test: H_0: RE, H_1: FE	0.85	0.75	1.12	1.07
R^2	0.77	0.63	0.76	0.77

Note: The panel model estimated is Z-score$_{(i=bank,t=time)} = \alpha + \sum_{j=1}^{10} \beta_j LA_{it,j} + \beta_{11}$ Loan loss provisions$_{it} + \beta_{12}$Size$_{it} + \beta_{13}$ Real GDP growth$_t + \beta_{14}$ Inflation$_t + \sum_{h=15}^{22} \beta_h$Time dummy$_t + \varepsilon_{it}$. LA is loans to assets for industry j. The Hausman F-test is based on equation (5.2). Serial correlation in model 2 is removed by data transformation using the approach in Baltagi and Li (1994) and Baltagi (2005, chapter 5.2). Heteroscedasticity consistent standard errors in parenthesis. ***,**,* means statistically significant at the 1, 5 and 10 per cent level.

Table 5.8: Sensitivity wrt. macroeconomic variables and customer composition for industries

	(5) RE Z-score	(6) RE Z-score	(7) RE Z-score	(8) RE Z-score	(9) RE Z-score
Measure of customer composition	LA	None	DSA	DSA	LA
Real estate	-0.0147 (0.0661)		0.0762 (0.0755)	0.0808 (0.0737)	-0.0182 (0.0696)
Financial leasing	-0.0766 (0.0806)		0.0724 (0.0927)	-0.0033 (0.0969)	-0.0139 (0.0891)
Farming	0.3106 (0.2446)		-0.1759 (0.2365)	-0.2338 (0.2537)	0.2614 (0.2444)
Other fin. service	-0.0100 (0.0761)		-0.0063 (0.0755)	0.0059 (0.0730)	0.0471 (0.0755)
Wholesale	-0.2736 (0.7178)		-0.0630 (0.6045)	-0.1417 (0.5000)	0.0921 (0.5556)
Bldg and constr	0.3601** (0.1555)		-0.2599 (0.2051)	-0.1988 (0.1865)	0.1855 (0.1460)
Investment funds	-0.2040 (0.1262)		0.0996 (0.1255)		
Mfr. of metals	-0.1818 (0.4127)		0.1451 (0.3509)		
Sale of motor veh.	1.5700** (0.6642)		-1.1113* (0.6649)		
Employees				0.0237 (0.0329)	0.0176 (0.0415)
Banks				-0.0043 (0.0320)	-0.0262 (0.0476)
Business activities				0.3345 (0.2588)	-0.4806* (0.2552)
Other industries	-0.0006 (0.0335)		0.0072 (0.0207)	-0.0197 (0.0331)	0.0511 (0.0536)
Loan loss provision	-526.4039 (340.3624)	-418.3563 (354.0840)	-440.6367 (369.7819)	-481.0768 (398.9254)	-472.0450 (410.5155)
Size, log(assets)	-1.9798*** (0.6364)	-2.7531*** (0.5677)	-2.4032*** (0.6581)	-2.5968*** (0.6993)	-2.5845*** (0.8466)
Real GDP growth		1.4577*** (0.1307)	1.4792*** (0.1324)	1.4571*** (0.1370)	1.4933*** (0.1414)
Inflation		0.9357* (0.5202)	0.9066 (0.5786)	0.9846* (0.5685)	0.8564 (0.6660)
Constant	37.9765*** (12.4566)	56.6215*** (9.6756)	49.8954*** (11.1931)	53.3413*** (11.7936)	52.8147*** (14.9280)
Time dummies	Yes	Yes	Yes	Yes	Yes
No of obs	164	164	164	164	164
No of banks	22	22	22	22	22
Wooldridge test for serial correlation	0.88	0.49	1.22	2.96	1.37
Wald-test for overall fit	364.28***	290.76***	357.53***	371.62***	328.14***
Hausman F-test: H_0: RE, H_1: FE	0.55	1.85	0.76	1.26	0.72
R^2	0.77	0.76	0.77	0.77	0.78

Note: LA (DSA) is loans (deposit surplus) to assets for industry j. The Hausman F-test is based on equation (5.2). Heteroscedasticity consistent standard errors in parenthesis. ***,**,* means statistically significant at the 1, 5 and 10 per cent level.

Table 5.9: Z-score components and solvency, data set on industries

	(10) RE ROAA	(11) RE Capital ratio	(12) RE Solvency	(13) RE sdROAA
LA, Real estate	-0.0384	-0.0048	-0.1160***	0.0055*
	(0.0357)	(0.0488)	(0.0430)	(0.0030)
LA, Financial leasing	-0.0069	-0.0215	-0.0598	-0.0002
	(0.0241)	(0.0554)	(0.0679)	(0.0047)
LA, Farming	0.1163***	0.1002	0.0484	0.0038
	(0.0337)	(0.1446)	(0.1246)	(0.0048)
LA, Investment funds	-0.0743**	-0.0137	-0.1423**	0.0123**
	(0.0373)	(0.0711)	(0.0669)	(0.0057)
LA, Other fin. service	0.0332*	0.0211	0.0400	-0.0078*
	(0.0193)	(0.0414)	(0.0596)	(0.0046)
LA, Wholesale	0.0133	-0.3779	-0.5605**	-0.0127
	(0.0937)	(0.3602)	(0.2766)	(0.0185)
LA, Bldg and constr	0.1954***	0.0156	0.1271	-0.0130*
	(0.0545)	(0.1206)	(0.1247)	(0.0067)
LA, Mfr of metals	-0.0057	0.1577	0.1876	-0.0018
	(0.0721)	(0.1863)	(0.1181)	(0.0168)
LA, Sale of motor vehicles	0.0597	0.8744**	0.2407	-0.0010
	(0.1354)	(0.3825)	(0.4443)	(0.0292)
LA, Other industries	0.0018	-0.0198	0.0296	0.0032*
	(0.0116)	(0.0146)	(0.0281)	(0.0018)
Loan loss provision	-59.2138	303.8013	-149.4848	69.0479***
	(134.4004)	(281.1288)	(355.1563)	(23.5058)
Size, log(assets)	-0.0443	-2.2937***	-0.3725	0.0248*
	(0.0967)	(0.4373)	(0.4524)	(0.0138)
Real GDP growth	0.2818***	0.144***	-0.2335*	-0.1013***
	(0.0505)	(0.0426)	(0.1335)	(0.0048)
Inflation	-0.2409	0.3441	0.0905	-0.1453***
	(0.1543)	(0.3364)	(0.3858)	(0.0267)
Constant	1.4479	47.5470***	19.3571**	0.7779**
	(2.0082)	(8.0332)	(8.3459)	(0.3053)
Time dummies	Yes	Yes	Yes	No
No of obs	164	164	164	164
No of banks	22	22	22	22
Wooldridge test for serial correlation	2.80	71.62***	7.72**	0.89
BGT_1-test, H_0: AR(1), H_1: MA(1)		-13.46***	-0.52***	
Wald-test for overall fit	157.70***	117.49***	45.93***	630.45***
Hausman F-test: H_0: RE, H_1: FE	1.14	1.03	0.94	1.07
R^2	0.64	0.44	0.25	0.72

Note: LA is loans to assets for industry j. The Hausman F-test is based on equation (5.2). The serial correlation in model 12 and 13 is removed by transformation of the data following the approach in Baltagi and Li (1994) and Baltagi (2005, chapter 5.2). Heteroscedasticity consistent standard errors in parenthesis. ***,**,* means statistically significant at the 1, 5 and 10 per cent level.

Table 5.10: Summary statistics, other measures of customer composition, data set on industries

Variable	N	Mean	Median	Min	Max	Std
Customer composition (based on DSA, DSA's)						
DSA, Real estate	164	-4.2732	-3.1816	-20.4199	0.9249	4.4084
DSA, Financial leasing	164	-2.0527	-0.4971	-13.6366	0.2067	2.8877
DSA, Farming	164	-1.6491	-0.7455	-10.7008	1.4188	2.4011
DSA, Investment funds	164	-1.2924	-0.2067	-15.8150	0.8703	2.6068
DSA, Other financial service activities	164	-1.3275	-0.4244	-20.8790	5.0861	3.3487
DSA, Wholesale	164	-1.1167	-1.0607	-5.7131	0.7280	1.0550
DSA, Building and construction	164	-0.9188	-0.5639	-7.9799	0.6891	1.3101
DSA, Mfr of metals and metal products	164	-0.6809	-0.4728	-8.9425	1.2786	1.1552
DSA, Sale of motor vehicles	164	-0.6365	-0.5772	-2.2895	0.0534	0.4964
DSA, Other industries	164	17.8321	16.9116	-45.2642	64.3739	16.3494
DSA, All industries	164	3.8842	5.7855	-74.6977	42.8098	19.2314
Customer composition (based on LA, DSA's)						
DSA, Employees etc.	164	10.4200	9.6645	-10.5863	60.1315	10.5663
DSA, Real estate	164	-4.2732	-3.1816	-20.4199	0.9249	4.4084
DSA, Banks	164	3.6974	2.4363	-24.2494	35.7076	7.5412
DSA, Farming	164	-1.6491	-0.7455	-10.7008	1.4188	2.4011
DSA, Business activities	164	0.0747	0.3922	-11.3738	3.3266	1.8870
DSA, Financial leasing	164	-2.0527	-0.4971	-13.6366	0.2067	2.8877
DSA, Building and construction	164	-0.9188	-0.5639	-7.9799	0.6891	1.3101
DSA, Wholesale	164	-1.1167	-1.0607	-5.7131	0.7280	1.0550
DSA, Other financial service activities	164	-1.3275	-0.4244	-20.8790	5.0861	3.3487
DSA, Other industries	164	1.0302	0.8205	-41.1331	38.0658	12.5852
DSA, All industries	164	3.8842	5.7855	-74.6977	42.8098	19.2314
Customer composition (based on LA, LA's)						
LA, Employees etc.	164	18.0543	17.3741	0.0000	60.8787	10.3952
LA, Real estate	164	6.7819	5.9402	0.1115	28.3612	5.1878
LA, Banks	164	4.0423	3.3793	0.0260	25.9389	3.5657
LA, Farming	164	3.1161	2.4943	0.0752	14.5123	3.1332
LA, Business activities	164	2.8856	2.5132	0.4883	11.3738	1.7296
LA, Financial leasing	164	2.1511	0.6110	0.0000	13.8684	2.9256
LA, Building and construction	164	2.0121	1.5001	0.0610	10.9861	2.0245
LA, Wholesale	164	2.0128	2.1343	0.0616	5.7131	1.2181
LA, Other financial service activities	164	1.8100	0.8716	0.0006	21.3397	3.3404
LA, Other industries	164	16.2799	15.5103	4.4845	42.7038	6.8827
LA, All industries	164	59.1460	60.8023	21.1773	106.2652	15.3928

Note: LA is lending to total assets. DSA is deposit surplus to total assets. Customer composition based on DSA, DSA's means that the most important industries is selected based on the average of deposit surplus to total assets and that the deposit surplus to assets is used as the proxy for customer composition. Customer composition based on LA, DSA's (Customer composition based on LA, LA's) means that the most important industries is selected based on the average of lending to total assets and that the deposit surplus (lending) to assets is used as the proxy for customer composition. Real estate is real estate activities and renting and Wholesale is expect motor vehicles.

Table 5.11: Correlations between explanatory variables, customer composition measured by deposit surplus to assets. Data set on industries

	DSA, Real estate	DSA, Fin. leasing	DSA, Farming	DSA, Inv. funds	DSA, OFSA	DSA, Wholesale	DSA, Bldg-constr
DSA, Real estate	1.00						
DSA, Fin. leasing	0.01	1.00					
DSA, Farming	-0.01	-0.08	1.00				
DSA, Inv. funds	0.31	0.25	0.13	1.00			
DSA, OFSA	0.06	0.05	-0.04	0.42	1.00		
DSA, Wholesale	0.20	-0.13	0.47	-0.19	-0.30	1.00	
DSA, Bldg-constr	0.59	-0.03	0.21	0.13	-0.13	0.14	1.00
DSA, Mfr of metals	0.36	-0.16	0.06	-0.15	-0.17	0.66	0.14
DSA, SMV	0.12	-0.15	0.17	-0.29	-0.32	0.40	0.27
DSA, Other indu.	0.21	-0.31	0.26	-0.25	-0.42	0.59	0.27
Loan loss	-0.04	-0.01	0.11	0.12	0.17	0.16	-0.01
Size	0.16	-0.13	0.17	0.11	0.09	0.02	0.23
Real GDP growth	0.04	-0.04	0.05	-0.01	-0.02	-0.04	-0.02
Inflation	0.02	0.05	0.06	-0.03	-0.08	0.09	-0.04

	DSA, Mfr of metals	DSA, SMV	DSA, Other indu.	Loan loss	Size	Real GDP growth	Inflation
DSA, Real estate							
DSA, Fin. leasing							
DSA, Farming							
DSA, Inv. funds							
DSA, OFSA							
DSA, Wholesale							
DSA, Bldg-constr							
DSA, Mfr of metals	1.00						
DSA, SMV	0.30	1.00					
DSA, Other indu.	0.60	0.31	1.00				
Loan loss	0.10	-0.18	0.06	1.00			
Size	-0.02	0.35	-0.19	-0.15	1.00		
Real GDP growth	-0.01	-0.03	-0.03	-0.20	-0.05	1.00	
Inflation	0.15	0.02	-0.02	0.01	0.02	-0.34	1.00

Note: DSA is deposit surplus to assets. Real estate is real estate activities and lending, Fin. leasing is financial leasing, Inv. funds is investment funds, OFSA is other financial service activities, Wholesale is wholesale except motor vehicles, Bldg-constr is building and construction, Mfr of metals is Mfr of metals and metal products and SMV is sale of motor vehicles and automotive fuel. Other indu. is other industries. Loan loss is loan loss provisions to assets. Size is measured by log(assets).

Table 5.12: Correlations between explanatory variables, alternative selection of most important industries.
Customer composition measured by deposit surplus to assets. Data set on industries

	DSA, Empl.	DSA, Real estate	DSA, Banks	DSA, Far-ming	DSA, Busi. act.	DSA, Fin. leasing	DSA, Bldg-constr
DSA, Empl.	1.00						
DSA, Real estate	0.22	1.00					
DSA, Banks	-0.19	-0.38	1.00				
DSA, Farming	0.22	-0.01	-0.16	1.00			
DSA, Busi. act.	0.37	0.39	-0.21	0.09	1.00		
DSA, Fin. leasing	-0.09	0.01	0.07	-0.08	-0.25	1.00	
DSA, Bldg-constr	0.34	0.59	-0.33	0.21	0.08	-0.03	1.00
DSA, Wholesale	0.36	0.20	-0.15	0.47	0.54	-0.13	0.14
DSA, OFSA	-0.53	0.06	-0.09	-0.04	-0.13	0.05	-0.13
DSA, Other indu.	0.03	0.36	-0.33	0.28	0.53	-0.29	0.30
Loan loss	0.07	-0.04	0.11	0.11	0.02	-0.01	-0.01
Size	-0.32	0.16	-0.22	0.17	-0.12	-0.13	0.23
Real GDP growth	0.06	0.04	-0.10	0.05	-0.01	-0.04	-0.02
Inflation	-0.08	0.02	0.03	0.06	0.07	0.05	-0.04

	DSA, Whole-sale	DSA, OFSA	DSA, Other indu.	Loan loss	Size	Real GDP growth	Infla-tion
DSA, Empl.							
DSA, Real estate							
DSA, Banks							
DSA, Farming							
DSA, Busi. act.							
DSA, Fin. leasing							
DSA, Bldg-constr							
DSA, Wholesale	1.00						
DSA, OFSA	-0.30	1.00					
DSA, Other indu.	0.51	0.03	1.00				
Loan loss	0.16	0.17	-0.03	1.00			
Size	0.02	0.09	0.21	-0.15	1.00		
Real GDP growth	-0.04	-0.02	-0.04	-0.20	-0.05	1.00	
Inflation	0.09	-0.08	0.02	0.01	0.02	-0.34	1.00

Note: DSA is deposit surplus to assets. Empl. is employees. Real estate is real estate activities and lending, Busi.act. is business activities, Fin. leasing is financial leasing, Bldg-constr is building and construction, Wholesale is wholesale except motor vehicles and OFSA is other financial service activities. Other indu. is other industries. Loan loss is loan loss provisions to assets. Size is measured by log(assets).

Table 5.13: Correlations between explanatory variables, alternative selection of most important industries.
Customer composition measured by loans to assets. Data set on industries

	LA, Empl.	LA, Real estate	LA, Banks	LA, Farming	LA, Busi. act.	LA, Fin. leasing	LA, Bldg-constr
LA, Empl.	1.00						
LA, Real estate	-0.13	1.00					
LA, Banks	-0.22	-0.15	1.00				
LA, Farming	0.21	0.03	-0.09	1.00			
LA, Busi. act.	-0.11	0.48	-0.14	0.01	1.00		
LA, Fin. leasing	-0.24	0.03	-0.02	-0.16	-0.17	1.00	
LA, Bldg-constr	0.17	0.64	-0.29	0.18	0.16	0.08	1.00
LA, Wholesale	-0.07	0.21	-0.14	0.48	0.55	-0.09	0.22
LA, OFSA	-0.17	0.00	0.12	-0.10	-0.27	0.11	-0.17
LA, Other indu.	-0.19	0.45	-0.12	0.40	0.56	-0.20	0.30
Loan loss	0.10	0.07	0.10	0.06	-0.01	0.01	0.09
Size	-0.67	-0.25	0.06	-0.28	0.00	0.14	-0.31
Real GDP growth	-0.02	-0.03	0.08	-0.06	0.03	0.03	0.05
Inflation	0.08	-0.02	0.10	-0.03	-0.11	-0.05	0.03

	LA, Wholesale	LA, OFSA	LA, Other indu.	Loan loss	Size	Real GDP growth	Inflation
LA, Empl.							
LA, Real estate							
LA, Banks							
LA, Farming							
LA, Busi. act.							
LA, Fin. leasing							
LA, Bldg-constr							
LA, Wholesale	1.00						
LA, OFSA	-0.38	1.00					
LA, Other indu.	0.60	-0.17	1.00				
Loan loss	-0.08	-0.07	-0.09	1.00			
Size	-0.06	-0.11	-0.12	-0.15	1.00		
Real GDP growth	0.05	0.02	-0.09	-0.20	-0.05	1.00	
Inflation	-0.09	0.07	-0.03	0.01	0.02	-0.34	1.00

Note: LA is lending to assets. Empl. is employees. Real estate is real estate activities and lending, Busi. act. is business activities, Fin. leasing is financial leasing, Bldg-constr is building and construction, Wholesale is wholesale except motor vehicles and OFSA is other financial service activities. Other indu. is other industries. Loan loss is loan loss provisions to assets. Size is measured by log(assets).

Table 5.14: List of industries in the data set on industries (in parenthesis: abbreviations used)

Farming
Fishing
Extraction of raw materials
Food, beverages, tobacco
Mfr. of textil, leather and footwear
Mfr. of wood and wood products, pulp, paper and paper products
Mfr. of chemical raw meterials, rubber and plastic products
Mfr. of glass and ceramic goods
Mfr. of metals and metal products (Mfr. of metals)
Mfr. of furniture and other industry
Production and distribution of electricity and water
Building and construction (Bldg and constr, Bldg-constr)
Sale of motor vehicles and automotive fuel (Sale of motor vehicles, Sale of motor veh.,SMV)
Wholesale except motor vehicles (Wholesale)
Retail sale and maintenance except motor vehicles
Hotels and restaurants
Transportation
Telecommunication and post
Central bank
Banks
Financial leasing (Fin. leasing)
Mortgage-credit institutes
Other credit institutes
Credit, other than credit institutes
CMO companies
Financing companies
Other financial intermediation
Investments associations
Innovacion companies
Investment funds (Inv. funds)
Venture companies
Investment managers
Financial holding companies
Other financial service activities (OFSA, Other fin. service)
Life insurance companies
Non-life insurance
Pension funds
Other pension insurance companies
Other insurance
Activities auxiliary to finance
Activities auxiliary to insurance
Real estate activities and renting (Real estate)
Business activities (Business act., Busi. act.)
Public and personal services
Education
Hospitals, medical, dental and veterinary activities
Social institutions
Recreational, cultural, sporting activities
Employees etc. (Employees, Empl.)
Domestic activity not stated

Note: Only the largest monetary and financial institutions, representing at least 95 per cent of the total balance sheet of the MFI-sector report their lending and deposits divided into industries. There are 50 industries in total and the classification is based on NACE (version 1.1, 2002).

Table 5.15: Summary statistics, sectoral data set

Variable	**N**	**Mean**	**Median**	**Min**	**Max**	**Std**
Z-score	196	11.8045	9.8987	0.0385	33.0773	6.6545
ROAA, per cent	196	1.4044	1.2957	-4.6998	4.2271	1.1785
sdROAA, per cent	196	0.9823	0.9682	0.6414	1.5010	0.2597
Capital ratio, per cent	196	9.3268	8.1492	3.0091	21.4839	4.4940
Solvency, per cent	196	12.6071	12.1000	8.3000	23.0000	2.4257
Customer composition (lending to assets, LA)						
LA, Households	196	21.3205	22.2464	0.0000	61.4851	11.9401
LA, Firms	196	36.9276	37.3776	6.0529	78.6501	14.3619
LA, MFIs	196	8.2916	5.3841	0.2232	32.6067	7.4621
LA, Government	196	0.8147	0.4647	0.0000	6.0121	1.0108
LA, All sectors	196	67.3544	67.8874	44.2848	86.7329	9.8728
Customer composition (Deposit surplus to assets, DSA)						
DSA, Households	196	9.8974	9.6763	-18.3894	61.1486	10.4453
DSA, Firms	196	-17.5171	-13.9744	-78.0623	8.1058	14.9974
DSA, MFIs	196	13.5649	11.4250	-16.3000	55.3025	13.4210
DSA, Government	196	0.9523	0.7236	-6.0121	8.1483	1.9903
DSA, All sectors	196	6.8974	7.0202	-74.4645	43.6157	18.8172
Bank characteristics						
Loan loss provision to assets	78	0.0007	0.0004	0.0000	0.0054	0.0008
Growth in loans, per cent	190	7.3858	6.9735	-12.1879	35.0565	8.9452
Size, log(assets)	196	10.1060	9.7029	7.9681	14.6208	1.5046
Size, share of assets	196	3.8657	0.6233	0.1481	49.0945	9.4260
Cost-income ratio	196	3.3856	1.7064	-35.5415	272.6656	19.7641
Large exposures to assets	148	0.0069	0.0048	0.0000	0.0336	0.0070
Macroeconomic variables						
Real GDP growth, y-y	9	1.2001	2.0587	-3.7570	2.7512	2.1324
Inflation, y-y	9	1.9994	2.2358	0.9231	2.5559	0.5788

Note: y-y means annual growth rates. The cost-income ratio is typically negative (or positive and huge) due to negative (small) revenues. Growth in loans is set to zero 6 times where the growth rate jumps up due to merger activity. Loan loss provisions and large exposures to assets are only reported by banks when relevant. The minimum values for loan loss provisions and large exposures are very small, but different from zero. The Z-score components, ROAA, sdROAA and capital ratio, are measured in per cent.

Table 5.16: Activities included in the sectors

Sector	**Activities included**
Households	Private individuals etc.
Firms	Non-financial corporations
	Other financial intermediaries and financial auxiliaries
	Insurance corporations and pension funds
	Self-employed individuals*
	Non-profit institutions serving households*
	Activities not allocated to any sector
Government	General government
MFIs	Monetary and financial institutions (central bank, banks, mortgage-credit institutes, other credit institutes and money market funds)

Note: Activities marked with * are included in the household sector in the official statistics. There are minor deviations in the statistics for the Household sector and the Employees industry due to errors and mistakes in the statistical reporting.

Table 5.17: Correlations between Z-score, Z-score components and solvency, sectoral data set

	Z-score	ROAA	Capital ratio	sdROAA	Solvency
Z-score	1.00				
ROAA	0.66	1.00			
Capital ratio	0.89	0.58	1.00		
sdROAA	-0.50	-0.24	-0.12	1.00	
Solvency	0.53	0.30	0.66	0.01	1.00

Table 5.18: Z-score and customer composition for sectors, preferred model and sensitivity wrt. bank characteristics

	(1) RE Z-score	(2) RE Z-score	(2') FE Z-score	(3) RE Z-score	(4) RE Z-score
LA, Households	0.1880***	0.1902*	0.1806*	0.2063***	0.1944***
	(0.0518)	(0.1055)	(0.1076)	(0.0521)	(0.0553)
LA, MFIs	0.0293	-0.0150	-0.0264	0.0201	0.0279
	(0.0350)	(0.0463)	(0.0484)	(0.0374)	(0.0352)
LA, Government	-0.1860	-0.0243	-0.0593	-0.2502	-0.2211
	(0.2261)	(0.2648)	(0.2614)	(0.2400)	(0.2147)
LA, Firms	0.0134	-0.1210*	-0.1339**	0.0223	0.0156
	(0.0276)	(0.0639)	(0.0661)	(0.0272)	(0.0302)
Loan loss provision	-399.4202	-1538.3728***	-1578.7347***		-343.1007
	(294.3577)	(298.7660)	(292.3205)		(273.9664)
Size, share of assets	-7.3034**	-14.1823	-13.7906		-8.9127***
	(2.8768)	(11.8547)	(21.3282)		(2.7540)
Cost-income ratio	-0.0050	-0.0118**	-0.0112**		-0.0055
	(0.0046)	(0.0057)	(0.0056)		(0.0047)
Growth in loans					0.0068
					(0.0249)
Large exposures					-35.5134
					(36.8742)
Real GDP growth	0.1691**	-0.0061	-0.0176	0.2162***	0.1672**
	(0.0693)	(0.0919)	(0.0948)	(0.0582)	(0.0733)
Inflation	-5.9820***	-2.5910***	-2.6350***	-6.1388***	-6.1182***
	(0.5919)	(0.3236)	(0.3177)	(0.5986)	(0.5753)
Constant	16.6892***	13.0273***	18.7645***	15.7492***	16.8664***
	(1.9662)	(3.7802)	(4.3019)	(1.9332)	(2.1024)
Time dummies	Yes	No	Yes	Yes	Yes
No of obs	196	196	196	196	196
No of banks	22	22	22	22	22
Wooldridge test for serial correlation	31.58***	137.19***		32.62***	32.19***
BGT_1-test:H_0: AR(1), H_1: MA(1)	-1.99***	-0.37***		-2.24***	-1.98***
Wald-test for overall fit (F-test for overall fit in (2'))	488.79***	129.26***	12.49***	503.80***	595.27***
Hausman F-test: H_0: RE, H_1: FE	0.02	3.43***		0.03	0.47
R^2	0.74	0.36	0.34	0.72	0.74

Note: The panel model estimated is Z-score$_{(i=bank,t=time)}$ $= \alpha + \sum_{k=1}^{4} \beta_j LA_{it,k} + \beta_5$ Loan loss provisions$_{it}$ + β_6Size$_{it}$ + β_7 Cost-income ratio$_{it}$ + β_8 Real GDP growth$_t$ + β_9 Inflation$_t$ + $\sum_{h=10}^{17} \beta_h$Time dummy$_t$ + ε_{it}. LA is loans to assets for sector k. The Hausman F-test is based on equation (5.2). The serial correlation is removed by transformation of the data following the approach in Baltagi and Li (1994) and Baltagi (2005, chapter 5.2). Heteroscedasticity consistent standard errors in parenthesis. ***,**,* means statistically significant at the 1, 5 and 10 per cent level.

Table 5.19: Sensitivity wrt. bank size, macroeconomic variables and customer composition for sectors

	(5) RE Z-score	(6) RE Z-score	(7) RE Z-score	(8) RE Z-score
LA, Households	0.1346**	0.1821***		-0.0743*
(DSA, Households in (8))	(0.0526)	(0.0526)		(0.0407)
LA, MFIs	0.0299	0.0272		-0.1032***
(DSA, MFIs in (8))	(0.0338)	(0.0366)		(0.0340)
LA, Government	-0.1388	-0.1556		-0.1513
(DSA, Government in (8))	(0.2135)	(0.2433)		(0.3347)
LA, Firms	0.0128	0.0105		0.0592**
(DSA, Firms in (8))	(0.0265)	(0.0279)		(0.0295)
Loan loss provision	-441.1359	-492.7669	1204.3621***	-865.1855***
	(307.0652)	(328.5417)	(446.0594)	(277.5537)
Size, share of assets		-8.6272**	-15.4089*	-19.7570**
		(3.5715)	(8.3924)	(7.9008)
Cost-income ratio	-0.0057	-0.0060	0.0024	0.0033
	(0.0045)	(0.0051)	(0.0055)	(0.0035)
Size, log(assets)	-2.6656**			
	(1.1219)			
Real GDP growth	0.1291*		0.4009***	0.1550**
	(0.0670)		(0.1076)	(0.0720)
Inflation	-4.9088***		-6.3480***	-5.5203***
	(0.6042)		(0.8029)	(0.6222)
Constant	43.1023***	2.1039	21.3143***	24.2860***
	(11.3361)	(1.9744)	(2.2553)	(2.2335)
Time dummies	Yes	Yes	Yes	Yes
No of obs	196	196	196	196
No of banks	22	22	22	22
Wooldridge test for serial correlation	41.15***	31.58***	24.79***	21.35***
BGT_1-test: H_0: AR(1), H_1: MA(1)	-1.86***	-1.99***	-1.64***	-1.76***
Wald-test for overall fit	522.67***	564.59***	252.65***	509.48***
Hausman F-test: H_0: RE, H_1: FE	0.01	0.08	0.02	0.00
R^2	0.76	0.75	0.63	0.76

Note: LA (DSA) is loans (deposit surplus) to assets for sector k. The Hausman F-test is based on equation (5.2). The serial correlation is removed by transformation of the data following the approach in Baltagi and Li (1994) and Baltagi (2005, chapter 5.2). Heteroscedasticity consistent standard errors in parenthesis. ***,**,* means statistically significant at the 1, 5 and 10 per cent level.

Table 5.20: Z-score components and solvency, sectoral data set

	(9) RE ROAA	(10) RE Capital ratio	(11) RE Solvency	(12) RE sdROAA
LA, Households	0.0084	0.0887***	0.0071	-0.0011
	(0.0119)	(0.0293)	(0.0376)	(0.0043)
LA, MFIs	-0.0170	0.0005	-0.0526*	0.0005
	(0.0159)	(0.0260)	(0.0282)	(0.0031)
LA, Government	-0.1399**	-0.0355	0.3136**	-0.0003
	(0.0616)	(0.1619)	(0.1482)	(0.0124)
LA, Firms	-0.0046	0.0246	-0.0503*	0.0062
	(0.0113)	(0.0177)	(0.0261)	(0.0047)
Loan loss provision	-132.4541	-29.2792	-22.6390	79.3437***
	(110.2274)	(255.6303)	(141.5208)	(22.9659)
Size, share of assets	0.3300	-8.7542***	16.3597**	0.1132
	(1.4639)	(3.1032)	(8.1768)	(1.0090)
Cost-income ratio	0.0044**	-0.0022	0.0405***	0.0005*
	(0.0018)	(0.0024)	(0.0034)	(0.0003)
Real GDP growth	0.2947***	0.1214**	-0.1283*	0.0464***
	(0.0522)	(0.0525)	(0.0778)	(0.0034)
Inflation	-0.3673***	-1.0482***	0.1048	0.2547***
	(0.0954)	(0.2392)	(0.2244)	(0.0071)
Constant	1.7613***	8.2741***	13.5900***	-0.3683*
	(0.5664)	(1.0397)	(1.9067)	(0.2161)
Time dummies	Yes	Yes	Yes	No
No of obs	196	196	196	196
No of banks	22	22	22	22
Wooldridge test for serial correlation	3.00*	14.79***	6.52**	2054.33***
BGT_1-test: H_0: AR(1), H_1: MA(1)	-0.92***	-2.96***	-1.20***	-3.81***
Wald-test for overall fit	303.94***	89.15***	133.58***	292.17***
Hausman F-test: H_0: RE, H_1: FE	0.00	0.23	0.02	0.33
R^2	0.61	0.33	0.43	0.63

Note: LA is loans to assets for sector k. The Hausman F-test is based on equation (5.2). The serial correlation is removed by transformation of the data following the approach in Baltagi and Li (1994) and Baltagi (2005, chapter 5.2). Heteroscedasticity consistent standard errors in parenthesis. ***,**,* means statistically significant at the 1, 5 and 10 per cent level.

Table 5.21: Correlations between explanatory variables, sectoral data set

	LA, Households	LA, MFIs	LA, Government	LA, Firms	Loan loss	Size, log(assets)
LA, Households	1.00					
LA, MFIs	-0.55	1.00				
LA, Government	-0.21	0.06	1.00			
LA, Firms	-0.40	-0.34	0.12	1.00		
Loan loss	0.09	0.00	0.06	-0.06	1.00	
Size, log(assets)	-0.74	0.80	0.20	0.01	-0.16	1.00
Size, share of assets	-0.40	0.75	0.14	-0.31	-0.15	0.77
Growth in loans	0.29	-0.19	-0.14	0.09	-0.07	-0.22
Large exposures	0.31	-0.42	-0.24	0.01	-0.04	-0.55
Cost-income ratio	0.27	-0.12	-0.05	-0.14	-0.04	-0.09
Real GDP growth	0.05	0.04	0.06	-0.04	-0.17	-0.08
Inflation	0.01	0.03	-0.06	0.02	-0.04	0.03

	Size, share of assets	Growth in loans	Large exposures	Cost-income ratio	Real GDP growth	Inflation
LA, Households						
LA, MFIs						
LA, Government						
LA, Firms						
Loan loss						
Size, log(assets)						
Size, share of assets	1.00					
Growth in loans	-0.18	1.00				
Large exposures	-0.33	0.11	1.00			
Cost-income ratio	-0.09	-0.06	0.02	1.00		
Real GDP growth	-0.02	0.39	0.09	-0.17	1.00	
Inflation	0.00	-0.02	-0.13	0.05	-0.34	1.00

Note: LA is loans to assets. Loan loss (Large exposures) is loan loss provisions (large exposures) to assets.

Table 5.22: Correlations between explanatory variables when customer composition is proxied by deposit surplus to assets, sectoral data set

	DSA, House-holds	DSA, MFIs	DSA, Govern-ment	DSA, Firms	Loan loss	Size, share of assets	Cost-income ratio	Real GDP growth	Infla-tion
DSA, Households	1.00								
DSA, MFIs	-0.49	1.00							
DSA, Government	-0.06	-0.05	1.00						
DSA, Firms	0.24	-0.31	0.41	1.00					
Loan loss	0.05	-0.21	-0.10	0.11	1.00				
Size, share of assets	-0.09	-0.11	-0.03	0.22	-0.15	1.00			
Cost-income ratio	-0.01	-0.04	0.05	0.12	-0.04	-0.09	1.00		
Real GDP growth	0.03	-0.02	-0.05	0.02	-0.17	-0.02	-0.17	1.00	
Inflation	-0.05	0.05	-0.02	-0.04	-0.04	0.00	0.05	-0.34	1.00

Note: DSA is deposit surplus to assets. Loan loss is loan loss provisions to assets.

Resume (in Danish)

Denne afhandling består af tre papirer indenfor emnerne betalingsformidling og finansiel stabilitet. De to første papirer handler om betalingssystemer, deres funktion og hvorfor banker benytter disse systemer til afvikling af betalinger. Det tredje papir omhandler sammenhængen mellem bankers finansielle stabilitet og sammensætningen af deres udlån.

Det første papir med titlen *The Topology of Danish Interbank Money Flows* (udarbejdet sammen med Morten L. Bech og publiceret i Banks and Bank Systems, Issue 4, 2009, s. 48-65) indeholder den første topologiske analyse af strømme af interbank-betalinger mellem danske banker. En voksende litteratur om betalingssystemers funktion baseret på den netværkstopologiske metode er kommet frem i de senere år, se bl.a. Soramäki et al. (2007).

Banker benytter betalingssystemer for store betalinger til at afvikle deres betalingsforpligtelser. Vores analyse er derfor baseret på et datasæt, der består af alle transaktioner i det danske betalingssystem for store betalinger i 2006. Formålet med betalingerne registreres ikke. Derfor benyttes en algoritme udviklet af Furfine (1999) til at opdele data i dag-til-dag lån i pengemarkedet og andre transaktioner. Algoritmen definerer en transaktion som et dag-til-dag lån hvis der på dag t er en transaktion fra bank A til bank B og en modsatrettet transaktion fra B til A på det samme beløb plus rentebetaling den følgende dag.

Vi identificerer to forskellige netværk. Det første netværk er pengemarkedsnetværket, der består af dag-til-dag lån i pengemarkedet. Det andet er betalingsnetværket bestående af alle øvrige transaktioner, primært afvikling af betalinger på vegne af bankkunder og bankernes egne betalinger.

Vi viser følgende resultater. For det første, er der flere aktive banker i betalingsnetværket end i pengemarkedsnetværket. For det andet, spiller to store kommercielle banker en stor rolle i begge netværk, men det er overraskende at det vigtige bank-par i betalingsnetværket *er forskelligt fra* det vigtige bank-par i pengemarkedsnetværket. For det tredje står de 10 vigtigste banker for en stor andel af den samlede værdi, der overføres mellem bankerne i begge netværk. Det er ret naturligt, da store banker har tendens til at være tættere forbundet til andre banker end de mindre banker. Det betyder, at begge netværk er ret koncentrerede. For det fjerde er den gennemsnitlige størrelse for en transaktion mellem de 10 vigtigste banker større i pengemarkedsnetværket end i betalingsnetværket. Når der tages højde for at to banker er forbundet hvis der er mindst én transaktion imellem dem, finder vi for det femte at der er få forbindelser som eksisterer hver dag.

Aktiviteten i netværkene er påvirket af sæsoneffekter. Betalingsnetværket udvides ved månedens eller kvartalets udgang og på den første åbningsdag efter en helligdag. I modsætning til dette, driver ugedagene sæsoneffekterne vi observerer i pengemarkedsnetværket.

I den sidste del af papiret ser vi på to forskellige begivenheder, et midlertidigt stop for afvikling af betalinger a) i betalingssystemet til afvikling af store betalinger og b) for en stor bank. Disse begivenheder ændrer strukturen i netværkene. Pengemarkedsnetværket udvides sådan at flere, men mindre værdifulde, dag-til-dag lån gennemføres. Aktiviteten daler i betalingsnetværket. Den anden begivenhed giver også anledning til akkumuleret efterspørgsel efter afvikling af betalinger.

Resultaterne viser at strukturen i disse to netværk er forskellig. Det er som forventet, idet typen af transaktioner i pengemarkedsnetværket er forskellig fra transaktioner i betalingsnetværket. Desuden påvirkes netværkenes struktur af sæsoneffekter og midlertidige stop for betalingsafviklingen.

Det andet papir har titlen *Competition from Settlement Banks in RTGS-Systems: The Case of Indirect Settlement* (udarbejdet alene). I dette papir defineres betalinger indenfor betalingssystemet som *direkte betalinger*, da en bank kan sende en betaling direkte til modtageren, mens *indirekte betalinger* er betalinger som afvikles via en afviklingsbank. Andre termer for dette fænomen er korrespondent-bankvirksomhed eller tiering. En afviklingsbank er en bank, som tilbyder afvikling af betalinger til andre banker. Dvs. den virker som bindeled mellem banker, der er medlemmer af betalingssystemet, og banker, der står udenfor.

Vi opstiller en model hvor et betalingssystem, et RTGS-system, og en afvik- lingsbank konkurrerer om at tilbyde afvikling af betalinger til to store og to små banker.

Alle banker kan afvikle indirekte via afviklingsbanken. Både betalingssystemet og afviklingsbanken maksimerer profit. Der er sekventiel prissætning sådan at RTGS-systemet fastsætter sin pris før afviklingsbanken.

Modellen i dette papir giver en ny måde til at analysere indirekte afvikling. Det antages, at der ikke er konkurrence mellem afviklings-institutionerne i Lai m.fl. (2006) og Adams m.fl. (2008). I disse papirer afvikles en andel af betalingerne indirekte. Derudover kan kun små banker vælge mellem direkte og indirekte afvikling og betalingssystemet er ikke modelleret eksplicit i Chapman m.fl. (2008). Som beskrevet, kan alle banker afvikle indirekte og betalingssystemet er et RTGS-system i dette papir.

Bankerne skal vælge enten direkte afvikling via betalingssystemet eller indirekte afvikling via afviklingsbanken. Vi ser bort fra bilateral udligning af betalinger mellem banker her. Bankernes valg af afviklings-institution afhænger af omkostningerne for betalingsafvikling i RTGS-systemet og afviklingsbanken. I RTGS-systemet består omkostningerne af en fast omkostning og et gebyr per transaktion. Der er faste omkostninger ved at benytte RTGS-systemet, men ingen faste omkostninger ved at benytte afviklingsbanken. Denne omkostningsstruktur betyder, at store banker med et stort antal betalinger foretrækker at betale en fast omkostning og et lavt gebyr per transaktion, dvs. store banker har præference for RTGS-systemet. Ud fra samme logiske tankegang, foretrækker de små banker afviklingsbanken.

Resultaterne viser, at der er tre markedsligevægte; 1) alle banker afvikler indirekte via afviklingsbanken, 2) alle banker afvikler direkte via RTGS-systemet eller 3) store banker med mange transaktioner afvikler direkte og små banker med få transaktioner afvikler indirekte. Der er dog kun to mulige ligevægte, 1) og 2), hvis afviklingsbanken får højere profit i 1) end i 3).

Markedsløsningen er inefficient i den forstand at den er forskellig fra en samfundsplanlæggers løsning. Dette skyldes de forskellige omkostninger i afviklings-institutionerne, der virker som en slags produktdifferenciering. RTGS-systemet og afviklingsbanken kan altså sætte priser, der er større end eller lig med marginalomkostningerne afhængigt af, hvor mange banker de servicerer. Inefficiensen reduceres med et omkostningsdækkende RTGS-system. En fuldt efficient markedsløsning kan opnås med et velfærds-maksimerende RTGS-system.

I en udvidelse af modellen kan bankerne og afviklingsbanken blive illikvide. Det betyder, at de kan være ude af stand til at afvikle betalinger. I forhold til markedsløsningen i grundmodellen, kan yderligere to situationer opstå. For det første, med en høj risiko for illikviditet er 2) og 3) de eneste mulige markedsligevægte. Dvs. at afviklingsbanken ikke tilbyder indirekte afvikling til de største banker. I den anden situation er der kun én mulig ligevægt, nemlig 4) store banker afvikler indirekte og små banker afvikler via betalingssystemet. Markedsløsningen afviger fra samfundsplanlæggerens løsning og dette er i overensstemmelse med grundmodellen.

Det tredje papir med titlen *Financial Soundness in Danish Banks: Does the Composition of Customers Matter?* er udarbejdet på egen hånd. Dette papir handler om relationen mellem bankernes kundesammensætning og deres finansielle stabilitet.

Som følge af den finansielle krise er bankernes eksponering mod bestemte kundegrupper kommet i fokus. Især er udlånet til ejendomsmarkedet og landbruget blevet nævnt for det danske bankmarked. Bankernes kundesammensætning er enten opdelt på bestemte brancher (*Udlejning og ejendomsformidling*, *Landbrug, gartneri og skovbrug*, *Bygge- og anlægsvirksomhed*, *Engros- og agenturhandel undtagen med biler* osv.) eller sektorer (*Husholdninger*, *Virksomheder*, *Offentlig forvaltning og service* samt *Monetære og finansielle institutioner*).

Så vidt jeg ved, er dette det første papir, som analyserer sammenhængen mellem bankernes finansielle sundhed og deres udlån til specifikke brancher og sektorer. Andre nylige studier indenfor dette område fokuserer på sammenhængen mellem bankers finansielle sundhed og a) konkurrence i banksektoren eller b) betydningen af bankernes størrelse og udenlandsk ejerskab af banker, se bl.a. Uhde and Heimeshoff (2009) og Fungáčová og Solanko (2008).

Datasættene er unikke. Vi har adgang til mikrodata for hver banks udlån opdelt på brancher og sektorer i perioden 2000-2008. Bankernes finansielle sundhed måles med den såkaldte Z-score metode. Vi kontrollerer for bank-specifikke variable og den makroøkonomiske udvikling, når vi estimerer sammenhængen mellem den finansielle sundhed og kundesammensætningen for bankerne.

Det første sæt af resultater er baseret på branche-data, da disse har den mest detaljerede opdeling af kundesammensætningen. Vi finder, at udlån til *Bygge- og anlægsvirksomhed* samt *Handel med biler, autoreparation, servicestationer* påvirker bankernes finansielle sundhed positivt. Betydningen af kundesammensætningen er dog overraskende lille. Det, der virkelig er vigtigt, er konjunktureffekter og bankernes størrelse. Bankerne er altså mindre finansielt stabile i en lavkonjunktur eller hvis de er store.

Resultaterne er relativt stabile overfor ændringer i de bank-specifikke eller makroøkonomiske variable, men følsomme med hensyn til kundesammensætningen.

Disse resultater bekræftes i datasættet for udlån til sektorer. Det er dog overraskende, at vi finder en signifikant effekt på bankernes finansielle sundhed fra udlån til *Husholdninger* foruden de signifikante effekter fra de makroøkonomiske variable og bankernes størrelse. Vi forventer at de brancher, der har betydning for bankernes finansielle sundhed svarer til de sektorer, der har en signifikant effekt.

Z-score målet kombinerer tre forskellige indikatorer for bankernes sundhed i ét mål. Der er to grunde til at tage underkomponenterne i betragtning. For det første kan vi opnå en forståelse af hvilke af underkomponenterne, der driver resultaterne for Z-scoren. For det andet kan vi undersøge hvor robust målet for finansiel sundhed er. Det har tendens til at være højt for banker med en stabil indtjening over tid og tendens til at være lavt for store banker. Så vi regresserer underkomponenterne i Z-score, bankernes profit, kapitalandele og volatiliteten af indtjeningen, på de foretrukne forklarende variable. Som et yderligere robusthedstjek af resultaterne for kapitalandele, regresserer vi også bankernes solvens på de foretrukne regressorer.

Flere brancher (*Landbrug, gartneri og skovbrug*, *Investeringsselskaber*, *Finansieringsvirksomhed i øvrigt*, *Udlejning og ejendomsformidling*, *Engros- og agenturhandel undtagen med biler* og *Andre brancher*) og sektorer (*MFI*, *Virksomheder*, *Offentlig forvaltning og service*) har signifikant effekt når vi ser på komponenterne i Z-score målet og solvensen. I branche-datasættet er resultaterne for den foretrukne model for bankernes sundhed drevet af to underkomponenter i Z-score målet, bankernes indtjening og deres kapital andele. I sektor-data er det kun kapital andelene, som driver resultaterne for Z-score målet.

Så selvom det empiriske vidnesbyrd kunne være stærkere, understøtter resultaterne Baselkomiteens synspunkt om, at det er vigtigt at holde rede på bankernes eksponering mod specifikke kundegrupper, herunder brancher og sektorer.

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