Peer monitoring or contagion? Interbank market exposure and bank risk

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Abstract

We test if interconnectedness in the interbank market is a channel through which banks affect each others riskiness. The evidence is based on quarterly bilateral exposures of all banks active in the Dutch interbank market between 1998 and 2008. A spatial lag model, borrowed from regional science, is used to test if z-scores of other banks affect individual banks z-scores through the network of the interbank market. Larger dependence on interbank borrowing and lending increases bank risk. But only interbank funding exposures to other banks in the system exhibit significant spill-over coefficients. Spatial lags for lending are insignificant while borrowing from other banks reduces individual bank risk if neighbors are stable, too. The positive effect of interbank funding on bank risk is strongest if these funds are obtained from stable banks in the periphery of it's network. Vice versa, stability shocks at interbank counterparties in the system spill over through the liability side of banks balance sheets.

Keywords: Interbank market, bank risk, spatial lag model
JEL classification: G21; L1

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1. Introduction

Interbank markets are pivotal for liquidity management purposes of financial institutions. They allow banks to buffer shocks by permitting a ready transfer of funds from surplus to deficit agents (Allen et al., 2009). At the same time, interbank markets represent complex networks, connecting all financial institutions in the banking system (Iori et al., 2008). This implies the danger of contagion through interbank linkages (Upper and Worms, 2004), with important implications for financial stability (Nier et al., 2007). To investigate if and to what extent interbank borrowing and lending affects individual bank risk, we borrow from spatial economics the simple notion that besides direct effects of interbank exposures on the risk of bank i, 'neighbors' matter, too. [1]

We suggest a simple method to investigate the direct and indirect effects of interbank activities on banking risk and specify a spatial lag model using the risk of all other banks $j \neq i$ weighted by their interbank market distance to test for an effect on the risk of bank i. Extending van Lelyveld and Liedorp (2006), we construct a data set covering quarterly interbank loans and deposits of all banks active in the Dutch interbank market between 1998 Q1 and 2008 Q4. While a number of empirical studies analyze pricing and trading volumes in national interbank markets, most studies fail to analyze the relative importance of other banks' risk in the system for banks' idiosyncratic risks. This paper therefore aims to complement the (still) relatively scarce empirical literature on the implications of interbank networks for bank risk.

Theoretically, the effect of interbank market exposures on bank risk remains ambiguous. Flannery (1996) and Rochet and Tirole (1996) emphasize potential positive effects from peer monitoring since banks are especially well equipped to assess other banks' risks. Thus, more interbank exposure would lead to lower bank risk ('peer-monitor' hypothesis). But Allen and Gale (2000) show that conditional on the structure of the interbank market, exposures can amplify liquidity shocks and thus contribute to banking system risk. In a complete system, i.e. where all banks are interconnected, liquidity shocks are more easily mitigated since the individual

[1] The notion that the network in which an individual unit operates is relevant too has been applied to, *inter alia*, social influence ("hypes"), job search, alliances and competition and transportation networks (Goyal, 2009).

burden remains small (Gai and Kapadia (2010)). However, if the structure of the interbank market is 'incomplete', i.e. banks hold claims only with selected counterparties, they show that the system's fragility is higher, too. [2] At the same time, also a complete system may pose risks if the shock is large enough. In such a case, the linkages between banks can act as a contagion channel and therefore higher interbank exposure would lead to higher bank risk ('contagion' hypothesis).

We test empirically whether interbank connectivity affects individual bank risk according to the 'peer-monitor' hypothesis or the 'contagion' hypothesis. While detailed interbank market data is becoming increasingly available, empirical evidence regarding these two hypotheses remains scarce. [3] Earlier evidence focused on pricing in the US Federal Funds market. Furfine (2001, 2002) confirms the 'peer-monitor' hypothesis because interest rates are found to reflect the credit risk of borrowing banks and, during crises, liquidity is still channeled to impaired banks affected by such shocks. However, a recent study of the Italian interbank market by Angelini et al. (2009), finds that only after the 2007/2008 financial crisis interbank interest rates came to depend on the creditworthiness of the counterparty. While Furfine explains observed interbank characteristics, he does not investigate further the risk implications of the existing exposure distribution for each bank individually. Likewise, Cocco et al. (2009) report for the Portuguese interbank market that relationships play a crucial role in determining both access to and the cost of funds. Such funds can substitute for costly information gathering, e.g. for small banks applying for funds, without establishing a relation to the intermediaries' idiosyncratic risk.

The paper closest to our study is Dinger and von Hagen (2009), who investigate explicitly the influence of interbank lending on the risk of commercial banks in 10 Central and Eastern European countries. They find, in line with the 'peer-monitoring' notion, that long-term interbank lending reduces bank risk, especially

[2] Freixas et al. (2000) provide a similar model of the interbank market with consumer induced shocks, arriving at the same conclusion that more complete interbank markets are less prone to systemic risk.

[3] A number of important studies use simulation and/or network methods to explore implications of interbank market structure. Iori et al. (2006) show that especially in heterogeneous banking markets, such as in The Netherlands, the role of the interbank market remains ambiguous. Nier et al. (2007) report, amongst other results, that increased connectivity has at first a positive effect on contagion risk, which, however, is reversed beyond a certain threshold level.

for small banks. While specifying exposures in the interbank market and carefully controlling for endogeneity, they do not further consider a bank's entanglement in the interbank market, as we do by means of the spatial lag. In this paper we seek to quantify the effect of the system's risk in addition to the direct effect documented by Dinger and von Hagen (2009). In addition, we complement the interbank market literature by explicitly assessing the relation between borrowing and risk. A novel element, compared to the extant literature, is the analysis of liability exposures or funding risks. This is a relevant channel as shown in a theoretical model by Huang and Ratnovski (2010). In their model wholesale funding might be withdrawn quickly on the basis of noisy public signals, thereby fostering inefficient liquidation that can jeopardize the stability of a bank. Another novel element in our paper is the inclusion of key network characteristics, namely the distinction into core and periphery banks.

We find, in contrast to Dinger and von Hagen (2009), that the relative size of both interbank lending and borrowing exposures increases the idiosyncratic risk of Dutch banks. In addition, our results further confirm the 'contagion' hypothesis since we find a significantly positive relation between the weighted risk of all interbank counterparties from which a bank borrows. Thus, deteriorating stability of industry peers also spills over negatively to an individual bank. In contrast, we do not find a significant relation between the weighted risk of all other banks with lending exposures after controlling for a number of bank-specific factors. Thus, we find direct evidence for a possible contagion channel only via the funding side of interbank markets, rejecting the 'peer-monitoring' hypothesis for the Dutch interbank market.

The remainder of the paper is structured as follows. In Section 2 we define a measure of bank risk, introduce the model to explain bank risk, and set out the different components of the model. We also present the methodology to estimate the interbank lending matrix which is part of the explanatory variables in the model. In Section 3 we present the data. In Section 4 we present the findings of our model. Robustness checks are shown in Section 5. Section 6 concludes.

2. Methodology

2.1. *Bank risk and determinants*

To examine the effect of interbank activities on bank risk we employ a panel data model with bank fixed effects to account for unobservable bank characteristics, such as ownership, and augment it with a spatial lag (Anselin, 1988).[4] Given the quarterly data on Dutch banks available it is natural to use a panel data model for this study. The baseline specification of the model is

$$y_{it} = \alpha_i + x_{it-1}\beta_1 + z_t\beta_2 + q_{it-1}\beta_3 + \varepsilon_{it}, \tag{1}$$

where y_{it} is the dependent variable, i.e. the risk of bank i in period t, and α_i denotes the unobservable bank i fixed effect. To mitigate possible endogeneity concerns, we lag all bank-specific, time-variant measures by one quarter.[5] x_{it-1} is the vector of bank specific covariates of bank i in period $t-1$, z_t is a vector of time-specific fixed effects in period t. Accordingly, q_{it-1} is the vector describing the interbank activities of bank i in period $t-1$. The remainder disturbance ε_{it} are assumed to be independent and identically distributed, iid $(0, \sigma_\varepsilon^2)$ and x_{it-1}, z_t and q_{it-1} are all assumed to be independent of ε_{it}.

We follow recent banking studies, e.g. Laeven and Levine (2009), and measure banking risk by their distance to default as suggested in Boyd et al. (1993).[6] Assuming that insolvency occurs when losses cannot be covered by equity, the probability of insolvency can be expressed as P($ROA < -CAR$) where CAR is the capital asset ratio. If we assume that return on assets (ROA) follows a normal distribution, z-scores calculated as $(ROA + CAR)/\sigma_{ROA}$ are inversely related to the probability of insolvency (Laeven and Levine, 2009). Thus, z-scores can be interpreted as the number of standard deviations that bank's return on assets has to fall below its ex-

[4] The inclusion of bank specific effects is based on the Hausman test: the null hypothesis that the estimates of the fixed effects model are equal to the estimates of a random effects model is rejected.
[5] We also ran instrumental variable regressions as robustness checks using lagged values as instruments as in Dinger and von Hagen (2009). Results were qualitatively unaffected.
[6] Alternative measures, such as CDS spreads, the share of non-performing loans or observed distress are only available for a smaller subset of the banks in our data.

pected value before equity is exhausted and the bank becomes insolvent. Higher z-scores therefore indicate less risky banks.

To choose risk-determinants $x_{i,t-1}$ from the virtually infinite universe of potential candidates, we borrow from the bank hazard literature and use so-called CAMEL covariates that proxy for banks' Capitalization, Asset quality, Managerial quality, Earnings and Liquidity for guidance (King et al., 2006).[7] In addition, we control for the relative importance of lending as opposed to other banking activities, novel lines of business, such as off balance sheet activities and bank size, measured as the natural logarithm of total assets. To control for business cycle effects, we specify a vector of year indicators.[8]

Capitalization *CAP* is measured as equity to total asset ratio. Moral hazard theory predicts that bank managers signal good prospects, in terms of anticipated higher revenues and lower costs, by choosing higher capitalization (Berger, 1995). Higher capital buffers reduce financial vulnerability, which would result in a positive coefficient (Mester, 1997). To measure asset quality we follow DeYoung (2003) and specify quarterly asset growth ($GRWTH$) to capture the risk of either expanding business activities too rapidly (leading to imprudent management of growth) or too slowly (falling behind in competing for market share). The second asset quality measure *LLR* relates loan loss reserves to equity. As high loan loss reserves may be associated with high expected credit risks we expect high values to be related to distress. This implies a negative coefficient. To proxy management quality we use the cost to income ratio (MGT) (see, for example, Wheelock and Wilson, 2000). Lower values of this variable indicate better management quality to control costs and raise revenues. So this variable should be negatively related. Earnings are measured by return on assets (*ROA*) and lower returns are expected to indicate higher likelihood of distress. As a second measure of earnings we use net interest income relative to total revenues (*II*). To measure liquidity risk (*LIQ*) we include the ratio of liquid liabilities (deposits and interbank liabilities) to total assets. The higher the ratio of liquid liabilities, the lower the direct funding risk as the bank can more easily fulfill withdrawal requests, so we expect a positive coefficient. The ratio of total

[7] In our analysis we used several definitions for each CAMEL covariate. Based on 1) availability, 2) highest univariate explanatory power, and 3) lowest correlation with other covariates, we selected the CAMELs described in this section.

[8] The F-test cannot reject the null hypothesis that all quarterly effects are zero. However the F-test rejects the null hypothesis that all year effects are zero.

Table 1
Independent variables: definitions and expected sign of coefficients

Variable	Definition	Expected sign
size	$ln(\text{total assets})$	$+$
CAP	$\frac{\text{total equity}}{\text{total assets}}$	$+$
$GRWTH$	quarterly asset growth	$+/-$
LLR	$\frac{\text{loan loss reserve}}{\text{total equity + loan loss reserve}}$	$-$
MGT	$\frac{\text{total cost}}{\text{total income}}$	$-$
ROA	return on assets	$+$
II	$\frac{\text{net interest income}}{\text{total revenues}}$	$+/-$
LIQ	$\frac{\text{liquid liabilities}}{\text{total assets}}$	$+$
$LOANS$	$\frac{\text{total loans}}{\text{total assets}}$	$+/-$
OBS	$\frac{\text{off balance sheet exposures}}{\text{total assets}}$	$+/-$
$exposurel$	$\frac{\text{total interbank lending}}{\text{total assets}}$	$-$
$exposureb$	$\frac{\text{total interbank borrowing}}{\text{total assets}}$	$-$
$foreignl$	$\frac{\text{total foreign interbank lending}}{\text{total interbank lending}}$	$-$
$foreignb$	$\frac{\text{total foreign interbank borrowing}}{\text{total interbank borrowing}}$	$-$
wzl	weighted risk of all banks to which a bank lends	$+$
wzb	weighted risk of all banks from which a bank borrows	$+$

loans to total assets (*LOANS*) indicates to what extent the bank relies on tradition intermediation activities as opposed to, for example, more fee- and capital income generating trading activities in securities. Higher loan-to-asset ratios indicate more credit risk but lower market risk, too. Hence, the expected sign is ambiguous. Finally, we include the ratio of off balance sheet exposures to total assets (*OBS*). More *OBS* activities may increase risk if they are poorly priced and primarily serve the purpose to generate fee income, e.g. in the form of flat fees on credit lines. Alternatively, *OBS* activities may be used actively by banks to hedge risks, e.g. using derivatives, which would reduce risk. The expected sign for this coefficient is therefore also ambiguous. The upper panel in Table 1 summarizes definitions and expectations of bank-specific covariates.

2.2. *Interbank activities*

Our main objective in this paper is to identify the effect of interbank market exposures on bank risk, specified in the vector q_{it-1}. A first innovation compared to previous literature is to distinguish interbank lending and interbank borrowing. In addition to analyzing credit risk of uncollateralized interbank loans (Upper and Worms, 2004), Huang and Ratnovski (2010) show that funding risk can be of equal importance. If banks rely on clustered wholesale funding by a few large counterparties in the interbank market, a sudden (confidence) shock due to a noisy public signal can induce failure to extend credit lines, especially since interbank exposures are usually short term. This can result in fire sales of assets at deep discounts, which could jeopardize the stability of the bank. [9] The current episode of financial instability provides anecdotal evidence in this regard. Hence, both interbank lending and interbank borrowing are important for bank risk. Although we have no high-frequency data available, which are a first starting point for such liquidity analysis, the interbank balances in our sample may give an indication of longer-term relationships in the interbank market following for instance Cocco et al. (2009). Loss of credit from these counterparties may affect the financial position of a bank adversely for a longer time period, if that bank also needs to find new counterparties.

We measure these direct effects of interbank lending and borrowing by including the share of bank i's aggregate interbank lending (borrowing) relative to the bank's total assets. Note that most of these funds have a maturity of less than three months. Negative coefficients would support the 'contagion' hypothesis to the extent that larger exposures imply an increased sensitivity of the bank's distance-to-default to relatively larger reliance on interbank activities.

Van Lelyveld and Liedorp (2006) identify foreign counterparties as the most important source of risk for the Dutch interbank market because problems with foreign banks affect all types of banks on the Dutch interbank market. Furthermore, Dutch banks are net borrowers on the international interbank market in each quarter (see below). To account properly for foreign counterparties, in terms of both

[9] Whether a bank is able to survive depends on its (liquid) buffers. See Zymek and van Lelyveld (2010) for a cross-country study of the determinants of liquidity buffers. Another reason why banks might hoard liquidity is because fire sales in a market provide excellent buying opportunities. Liquidity is then at a premium (cf Acharya and Merrouche (2009)).

lending and borrowing, we include the share of bank i's foreign interbank lending (borrowing) relative to bank i's total interbank lending (borrowing). In line with van Lelyveld and Liedorp (2006), we expect a negative coefficient for both variables: more exposure to foreign counterparties is more risky.

A second innovation is our measurement of indirect effects of interbank activities as determinants of bank risk. To this end, we borrow from the spatial economics literature. In spatial economics, one usually includes spatial lags which reflect the relative position (for example, measured by distance or travel time) of one unit of analysis, e.g. a region, to another. We specify a spatial lag such that z-scores of the 'neighboring' bank in the interbank market spill over to bank i. Here, we weigh z-scores of all other banks by their exposure in the interbank matrix. The number of banks active in the interbank lending market varies over time, we assume that entry and exit in this market is exogenous. Explicit incorporation of the entry and exit decision in the model is beyond the scope of this paper. We do test the sensitivity of our results to this assumption by estimating our model on a subsample of banks that are present in the market in all periods in section 5. We let wzl_{it-1} and wzb_{it-1} denote the weighted average of bank risk across all banks with which bank i maintains relations. The additionally estimated parameters of these variables measures if bank risk is reduced (positive coefficient), increased (negative coefficient), or independent (coefficient equal to 0) from the riskiness of other banks in the system. [10] The bottom panel in Table 1 summarizes these interbank measures.

2.3. *Constructing the interbank lending matrix*

Construction of the interbank lending matrices is central to our study. To model the structure of the interbank linkages in period t we use a matrix like M_t in Equation (2). In M_t the columns represent banks' lending and the rows represent banks' borrowing. Hence, $m_{t,ij}$ represents the lending of bank i towards bank j with $i, j = 1, \ldots, n_t$, where n_t denotes the total number of banks in period t. The matrix

[10] Spatial econometrics made important advances and by now provides a number of more sophisticated estimators to account for spatial (i.e. interbank) correlation, see for example Elhorst (2008). While distances remain constant, interbank market exposures naturally fluctuate over time and banks. Therefore, and in contrast to most regional applications, our weighting matrix changes over time, which is not yet considered in most recently developed spatial estimators. For this reason we opted here for a simple spatial lag model.

also includes lending to foreign banks (column (n_t+1)) and borrowing from foreign banks (row (n_t+1)). For $i, j = 1, \ldots, n_t$ column sums $a_{t,i} = \sum_{i=1}^{n_t+1} m_{t,ij}$ represents bank i's total lending towards all other banks (domestic and foreign), and row sums $l_{t,j} = \sum_{j=1}^{n_t+1} m_{t,ij}$ represents bank j's total borrowing from all other banks (domestic and foreign). The total lending and borrowing of bank i in period t are known. As foreign banks do not report to DNB, the total borrowing and lending of foreign banks are not known. However, we observe the large exposures of each individual bank towards the total of foreign banks. Therefore, we can proxy the total borrowing from foreign banks by all Dutch banks in the system. [11]

In terms of the matrix M_t we know all the row and column totals but do not know the individual elements $m_{t,ij}$. In absence of further information, Wells (2004) suggests to divide all exposures evenly across all counterparties (i.e. entropy maximization. See appendix A.1 for a short explanation). However, we can improve the estimation as we have a prior about the distribution based on the large exposures data, (see van Lelyveld and Liedorp, 2006). Additionally, the main diagonal of the matrix is zero since banks cannot lend to or borrow from themselves. Using this information, we need to find a solution that distributes the column and row totals over the matrix, which stays as close to the distribution of the prior as possible. This is a mimimization problem that can be solved by the RAS algorithm. The algorithm iteratively uses column and row constraints. The starting values are given by the matrix M_t^0, as shown by Blien and Graef (1997). Given the constraints posed by the large exposures data and with a few additional assumptions, we solve the minimization problem. [12]

[11] This supposes a closed system.

[12] When estimating the interbank matrix, we assume that all banks are interlinked. We replace all zeros in the matrix, except for those on the main diagonal, with a very small number to prevent gridlock using the RAS algorithm (see also appendix A.1). Since the large exposure reporting framework has a reporting threshold, some of these bilateral positions will actually exist. In analysing the number of linkages in the interbank market, we disregard these small-sized linkages in order to focus on the most important relationships for a bank.

$$
\begin{array}{lcc}
 & & \Sigma_j \\
M_t = & \left(\begin{array}{ccc|c} m_{t,11} & \cdots & m_{t,1n_t} & m_{t,1(n_t+1)} \\ \vdots & \ddots & \vdots & \vdots \\ m_{t,n_t1} & \cdots & m_{t,n_tn_t} & m_{t,n_t(n_t+1)} \\ \hline m_{t,(n_t+1)1} & \cdots & m_{t,(n_t+1)n_t} & m_{t,(n_t+1)(n_t+1)} \end{array}\right) & \begin{array}{c} l_{t,1} \\ \vdots \\ l_{t,n_t} \\ l_{t,(n_t+1)} \end{array} \\
\Sigma_i & \begin{array}{cccc} a_{t,1} & \cdots & a_{t,n_t} & a_{t,(n_t+1)} \end{array} &
\end{array} \tag{2}
$$

To test whether the risk of bank i depends on the risk of all other banks to which bank i lends and on the risk of all banks from which bank i borrows (as explained in Section 2.2), we interpret M_t^* as a weight matrix. We weigh the z-scores of all other banks by their exposures in the normalized M_t^*.

3. Data

The data set is constructed from consolidated financial accounts, solvency figures and large exposures reported quarterly to the Dutch supervisor DNB by all banks active in the Netherlands. For the large exposure data, banks report all risks larger than 3% of own funds on bank counterparties and risks larger than 10% of own funds on non-bank counterparties. [13] These data are reported per counterparty (name basis). The reports are not complete, in particular off-balance sheet positions are not included. Furthermore, banks sometimes report only risk limits instead of outstandings. From the large exposures report, the gross exposures on home (Dutch) and foreign (non-Dutch) bank counterparties are selected. [14] Data are available from 1998 Q1 to 2008 Q4, with the number of reporting banks varying from 91 to 102. A core of 50 banks report every quarter during the sample period. [15]

[13] Note that branches of banks located in the EU (type 4) and holding companies are exempted from reporting large exposures data.
[14] Using net exposures does not impact the analysis.
[15] We assume that exit and entry on the interbank market is exogenous.

Table 2
Number of banks per type (range), 1998 Q1 2008 Q4

Large bank	Other NL banks	Foreign subsidiary	Foreign branch	Investment firm	Total
5	31-36	23-33	20-32	3-8	91-102

Banks active on the Dutch market differ in many respects, such as size, activities, origin and legal status. This may impact their behavior on the interbank market. Therefore, we distinguish five types of banks. The largest five banks constitute the first type of banks. They are considerably larger than the other banks and account for approximately 85% of aggregate interbank assets. The second type of banks are the remaining Dutch banks. Foreign subsidiaries supervised by DNB constitute type 3. These entities have a separate legal status and hence have to comply with all solvency and liquidity requirements in the host country (in this case The Netherlands). Type 4 banks are the branches of foreign banks. These banks do not have a separate legal status, but are legally part of the bank holding company in the home country. Foreign branches of bank holding companies within the European Union do not report solvency figures since DNB plays no role in the solvency supervision of these banks. Investment firms, which provide services markedly different from traditional banking operations, constitute type five. Table 2 shows the range (over time) of the number of banks by type. [16]

3.1. z-score

As a measure of bank risk we use the z-score, which is defined as z-score $=$ $(ROA + CAR)/\sigma_{ROA}$. The standard deviation of the return on assets is based on the previous four quarters. As a consequence, the z-score cannot be calculated for the first year 1998. The z-score fluctuates noticeably over time and between bank types (see Figure 1 and Table 3). This suggests there is enough variation in our dependent variable to be explained by our model. The range of the z-scores we find for the banks in the Dutch interbank market is similar to the range reported in the literature (for example see Boyd et al. (2006), or Mercieca et al. (2007)).

[16] We focus on types 1 through 4. Type 5 banks are unimportant on the interbank market.

Fig. 1. Development of z-score over time

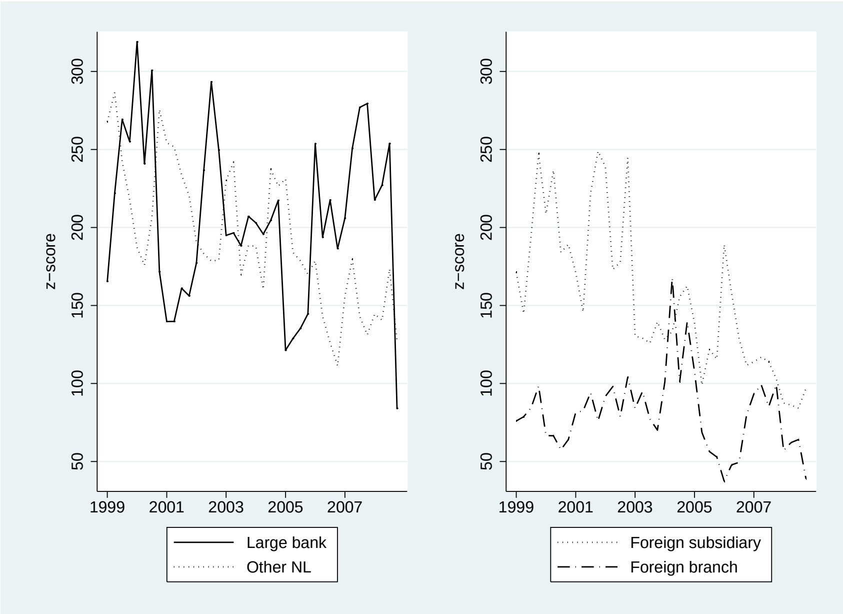


Table 3
Descriptives by type z-score, 1999 Q1 2008 Q4

type	mean	sd	N
Large banks	207.1	182.7	200
Other NL banks	194.0	257.9	1274
Foreign subsidiaries	156.8	230.8	988
Foreign branches	80.5	141.8	1051
Investment firms	53.0	76.0	196
Total	145.2	218.0	3709

3.2. Bank specific covariates

The descriptive statistics for the bank specific covariates are shown in Table 4. Large banks have the highest leverage ratio. Furthermore, their annual asset growth seems modest, while loan loss reserves are rather high compared to other banks. In terms of efficiency, large banks score lower than many other banks as well. Foreign subsidiaries turn out to be the most efficient banks in the Netherlands. Notwithstanding the booming asset markets, especially in the second half of the data period, interest income is still the most important source of income for most banks, representing just more than half of total income. This also follows from the fact that for almost all banks in the Netherlands, lending is still the most important activity. At the same time, we see that off balance sheet exposures can be significant for some banks.

Table 4
Descriptives by type covariates, 1998 Q4 2008 Q3

type	stats	*CAP*	*GRWTH*	*LLR*	*MGT*	*ROA*	*II*	*LIQ*	*LOANS*	*OBS*
Large banks	mean	3.8	3.4	12.4	74.4	3.2	60.6	65.7	73.5	23.6
	sd	1.0	7.3	6.1	25.5	2.6	18.3	10.9	11.4	12.6
	N	200	200	200	200	200	200	200	200	185
Other NL banks	mean	11.5	3.9	6.3	64.4	2.8	60.1	65.3	71.4	15.4
	sd	15.4	20.0	9.4	71.1	5.5	41.6	28.9	26.1	51.3
	N	1344	1329	1296	1309	1344	1309	1344	1344	1247
Foreign subsidiairies	mean	17.4	5.1	7.3	56.8	4.5	69.5	77.0	75.6	45.8
	sd	23.8	23.5	13.3	64.3	14.6	38.4	24.6	26.7	117.0
	N	1047	1034	1001	1032	1047	1032	1047	1047	968
Foreign branches	mean	8.7	9.7	7.4	100.0	9.2	58.1	85.2	84.2	33.4
	sd	18.4	40.4	13.5	135.9	24.4	39.3	23.5	24.2	83.1
	N	1138	1113	948	1086	1028	1086	1138	1138	1039
Investment firms	mean	16.7	2.3	0.7	85.9	5.9	11.6	73.3	63.9	2.0
	sd	18.0	24.8	1.4	50.0	13.4	9.6	26.6	25.0	3.9
	N	201	201	192	198	201	198	201	201	192
Total	mean	12.1	5.8	6.9	74.1	5.2	59.6	74.6	75.9	28.4
	sd	19.0	28.2	11.5	92.5	15.7	40.0	26.8	25.8	82.0
	N	3930	3877	3637	3825	3820	3825	3930	3930	3631

Notes: *CAP*: inverse leverage ratio, *GRWTH*: asset growth, *LLR*: loss reserve ratio, *MGT*: cost to income ratio, *ROA*: return on assets, *II*: interest income ratio, *LIQ*: liquid liabilities ratio, *LOANS*: loan ratio, *OBS*: off balance sheet ratio

3.3. The interbank market

In 1998, the Dutch interbank market covered about EUR 219 billion of interbank assets (17% of total assets) and EUR 339 billion of interbank liabilities (26% of total assets). Over time, the interbank assets and liabilities of Dutch banks have grown, and at the beginning of 2007 exposures were more or less twice as large as at the beginning of the data period (see Figure 2). In relative terms however, interbank assets and liabilities declined as a percentage of total assets over time (see Figure 3). At all times though, interbank liabilities exceed interbank assets. Thus, Dutch banks are net borrowers on the international interbank market. In terms of capital, interbank assets (liabilities) are on average four (six) times Tier 1 capital.

These developments are dominated by a few large banks, which cover about

Fig. 2. Growth of interbank assets and liabilities (indexed)

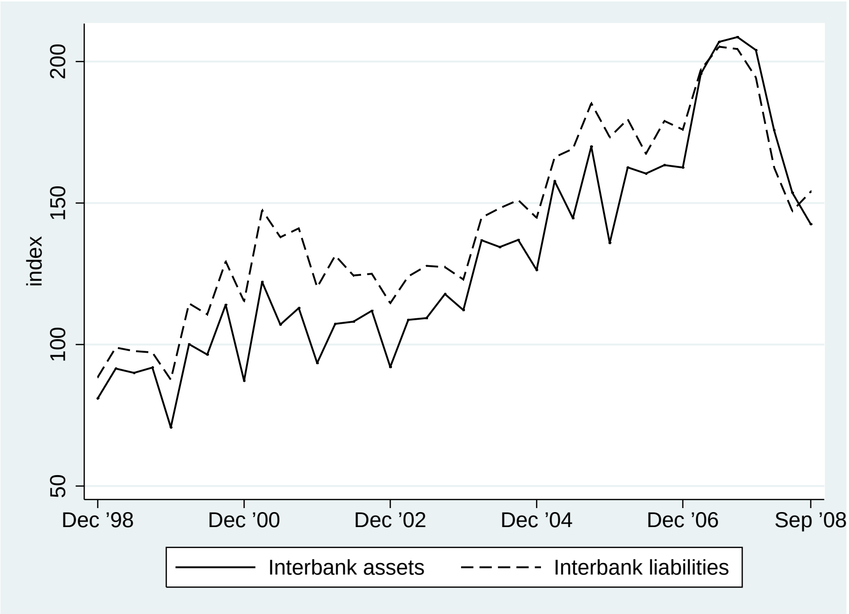
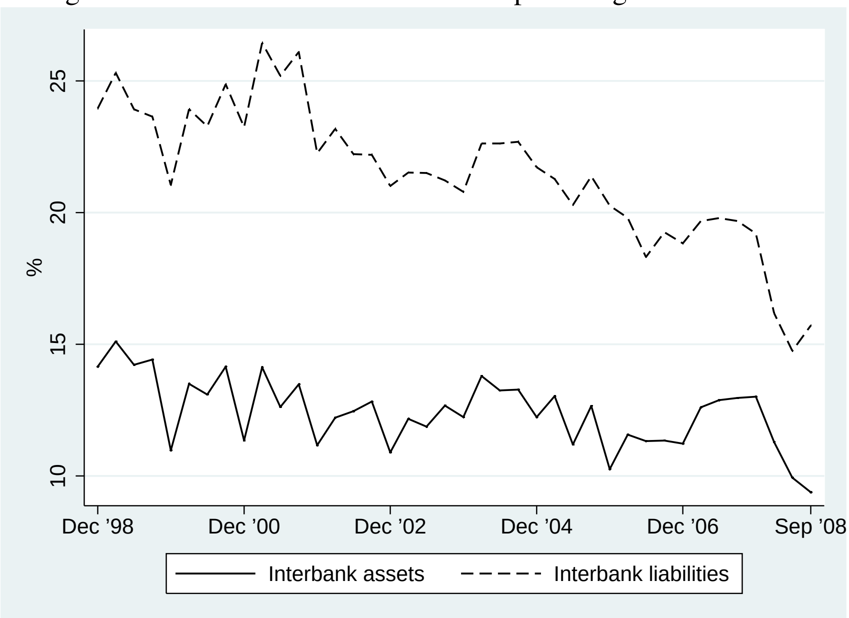


Fig. 3. Interbank assets and liabilities as percentage of total assets



80% of interbank assets and liabilities. Table 5 provides descriptive statistics for the different types of banks, highlighting that large banks' interbank liabilities are on average larger than interbank assets. Interbank assets amount to EUR 46 billion on average (12% of total assets), whereas interbank liabilities stand at EUR 82 billion (22% of total assets). Hence, many of the larger banks rely on foreign funding.

To estimate Equation (2), for each period we construct the largest possible dataset of both interbank assets and liabilities and large exposures data. The dimension of

Table 5
Descriptive statistics by type, balance sheet data (in EUR million), 1998 Q4 2008 Q3

type	stats	Interbank assets	Interbank liabilities	Total assets
Large banks	mean	45548	81587	392469
	sd	36131	58009	307111
	N	200	200	200
Other NL banks	mean	794	1189	8759
	sd	1843	2660	15129
	N	1344	1344	1344
Foreign subsidiaries	mean	396	495	1426
	sd	516	758	1520
	N	1047	1047	1047
Foreign branches	mean	699	880	1227
	sd	1863	2130	2650
	N	1138	1138	1138
Investment firms	mean	58	98	299
	sd	52	220	291
	N	201	201	201
Total	mean	2900	4951	23719
	sd	12882	22123	110287
	N	3930	3930	3930

the matrix M_t therefore changes over time (see also Table 2). Important characteristics of the market's structure are the number of linkages between banks, the size of these linkages and the type of counterparts.

The number of counterparties a bank lends to on the interbank market is different across types of banks. On average, large banks interact with 17 to 57 different counterparties, depending on the sample period. This number is increasing over time. Having many different counterparties reduces the credit risk on one party and hence reduces concentration risk. At the same time however, it may increase contagion risks. The number of counterparties of other Dutch banks or foreign banks is much lower and varies significantly over time and between bank types. The interbank matrices also show that the different types of bank interact with different counterparties. Large banks mainly lend to foreign banks, covering around 80% of their total interbank exposure over time. Averaging 20% of their total exposures, their lending to other banks is modest and stable over time. Counterparties of other Dutch banks differ over time. Their most important counterparty are the large banks, representing between 23% and 60% of exposures. Foreign subsidiaries in the Dutch market are primarily exposed to foreign banks, representing over half of their total interbank assets. This is likely to reflect exposures to holding companies abroad.

From a borrowing perspective, the interbank matrix shows for almost all banks that the number of counterparties decreases over time. Large banks borrow on average from 17-59 counterparties, depending on increasingly fewer counterparts for funding. This trend is amplified for other Dutch banks, for which the average number of counterparties falls from 32 in 1998 to only 4 by 2008. In terms of counterparty types, we find that the largest Dutch banks mainly borrow from their foreign counterparts, which account for 80% of their total interbank borrowing. Borrowing from other large banks and Dutch banks is low. Foreign subsidiaries also depend mainly on foreign financing (40% to 80% of borrowing). For other Dutch banks, almost 50% of borrowing is from other Dutch banks prior to 2002. Thereafter, foreign banks take over the role of largest funder, accounting for more than 80% in 2008. Foreign branches are largely dependent on the large Dutch banks for their financing needs, which represent almost 80% of their total borrowing in the beginning of the data period in 1998.

3.4. Data caveats

Inevitably, the construction of the interbank matrix is to a certain degree heuristic. A first important caveat is that interbank exposures exhibit end-of-year effects: the interbank exposures decline every fourth quarter. In the robustness analysis in Section 5 we check for such characteristics by either including a dummy or leaving out fourth quarter observations. Second, large exposure reports do not include off-balance sheet positions. This may underestimate the contagion risk. Furthermore, banks sometimes report risk limits instead of outstandings. To avoid bias towards banks that report limits we converted the large exposures data to percentages (see Section 2.3). Finally, not all banks are obliged to report the large exposures data. For missing exposures, the interbank assets are divided evenly across all possible counterparties, which is the best proxy if no further information on the dispersion of interbank exposures is available (i.e. maximum entropy). However, this results in an overrepresentation of exposures on Dutch banks, especially for foreign branches since these banks are not obliged to report large exposures data. To see how this affects the model we employ a robustness check in which we include only banks which are subject to the full supervision of DNB.

4. Results

Consider the baseline estimation results shown in Table 6. The coefficients have been estimated by a standard fixed effects panel data estimator. This is appropriate because endogeneity of the interbank lending variables disappears by taking lagged values as covariates. Since we employ the fixed effect estimator, we allow for unobserved bank-specific effects that are correlated with the observed covariates. Also, our estimation method only allows us to identify the effect of time-varying covariates which is not restrictive considering the dynamic structure of our dataset. Column 1 shows the model including the main effects of interbank lending, namely the relative importance of interbank lending $exposurel$, the risk of counterparties wzl, and foreign exposures $foreignl$. In the next column, we check whether the impact differs per bank type and include the interaction effect between the risk of neighboring banks to which a bank lends (wzl) and bank type. In columns 3 and 4 we sequentially examine the effect of interbank borrowing and interaction effects. Finally, in column 5 we examine the effect of interbank lending and interbank borrowing simultaneously. Column 6 presents the full model that takes interaction effects with bank type into account, too.

Table 6
Estimation results baseline model

VARIABLES	(1) *wzl*	(2) *wzl**type	(3) *wzb*	(4) *wzb**type	(5) *wz*	(6) *wz**type
size	−7.1901	−7.1189	−1.6490	−2.4744	−7.0804	−7.6291
	[7.6714]	[7.5875]	[7.6578]	[7.7437]	[7.7307]	[7.6621]
CAR	3.7276***	3.7547***	3.3184***	3.3514***	3.5995***	3.6167***
	[0.9560]	[0.9529]	[0.8699]	[0.8730]	[0.9030]	[0.8960]
GRWTH	−0.2639**	−0.2700**	−0.3225***	−0.3301***	−0.2756**	−0.2934**
	[0.1198]	[0.1195]	[0.1185]	[0.1190]	[0.1211]	[0.1212]
LLR	−1.5814*	−1.6123*	−1.4054*	−1.3337	−1.4914*	−1.4645*
	[0.8277]	[0.8329]	[0.8310]	[0.8075]	[0.8353]	[0.8291]
MGT	−0.0632**	−0.0616**	−0.0633**	−0.0663**	−0.0649**	−0.0662**
	[0.0283]	[0.0273]	[0.0294]	[0.0299]	[0.0286]	[0.0280]
ROA	−5.8687*	−5.8162*	−6.5829*	−6.6042*	−6.0971*	−6.1486*
	[3.4095]	[3.3734]	[3.4145]	[3.4519]	[3.3440]	[3.3405]
II	0.2660**	0.2642**	0.2698**	0.2738**	0.2834**	0.2880***
	[0.1092]	[0.1085]	[0.1116]	[0.1094]	[0.1085]	[0.1055]
LIQ	2.6995***	2.7107***	3.0113***	3.0061***	2.9154***	2.9382***
	[0.7499]	[0.7389]	[0.7620]	[0.7679]	[0.7340]	[0.7315]
LOANS	0.5769	0.6058	−0.1293	−0.1174	0.5637	0.5784
	[0.6591]	[0.6348]	[0.7195]	[0.7074]	[0.6419]	[0.5930]
OBS	−0.0047	−0.0047	−0.0668	−0.0678	0.0164	0.0151
	[0.0993]	[0.0999]	[0.0934]	[0.0936]	[0.0940]	[0.0949]
exposurel	−1.3845***	−1.4006***			−1.3934***	−1.3720***
	[0.4827]	[0.4787]			[0.4811]	[0.4701]
foreignl	−0.0543	−0.0723			0.0335	0.0080
	[0.1920]	[0.1952]			[0.2225]	[0.2273]
wzl	−0.0488	0.3058			−0.0509	0.1842
	[0.0492]	[0.2322]			[0.0498]	[0.1735]
*type*2 × *wzl*		−0.3520				−0.2455
		[0.2457]				[0.1935]
*type*3 × *wzl*		−0.3971				−0.2770
		[0.2535]				[0.2022]
*type*4 × *wzl*		−0.3543				−0.2256
		[0.2506]				[0.1946]
*type*5 × *wzl*		−0.2612				−0.1337
		[0.2367]				[0.1815]
exposureb			−0.5125*	−0.4938*	−0.5604**	−0.5843**
			[0.2720]	[0.2698]	[0.2753]	[0.2800]
foreignb			−0.2423	−0.1797	−0.2377	−0.1634
			[0.1866]	[0.1882]	[0.2006]	[0.1998]
wzb			0.0264	2.0248*	0.0308	1.7743*
			[0.0632]	[1.1398]	[0.0595]	[1.0702]
*type*2 × *wzb*				−1.8694		−1.6115
				[1.1457]		[1.0775]
*type*3 × *wzb*				−2.1603*		−1.8631*
				[1.1404]		[1.0709]
*type*4 × *wzb*				−2.1466*		−1.9056*
				[1.1360]		[1.0673]
*type*5 × *wzb*				−1.5827		−1.3969
				[1.2048]		[1.1356]
Observations	3330	3330	3330	3330	3330	3330
R-squared	0.042	0.044	0.036	0.041	0.044	0.050
Number of inst	135	135	135	135	135	135

Robust standard errors in brackets, $***p < 0.01, **p < 0.05, *p < 0.1$.

4.1. *Bank Specific Covariates*

Table 6 shows that the vast majority of all bank specific covariates is (highly) significant at the 1% level, except for the effect of bank size, which is insignificant. The coefficients of *CAP*, *LLR* and *MGT* have the expected sign. The effect of quarterly asset growth (*GRTWH*) is found to be negative. A possible reason for this effect is that banks may expand their activities faster than they can acquire necessary product or process skills (see also DeYoung, 2003), which may imply the accumulation of higher risks compared to more experienced peers. The negative coefficient of profitability (*ROA*) may simply indicate that the realization of higher returns requires to take also riskier positions. [17] Larger shares of interest income relative to total revenues reduce the riskiness of the bank, as shown by the positive coefficient of the effect for *II*. While eroding margins in banking may result in lower levels of earnings, this result could indicate that lower volatility of earnings due to a relatively large share of rather steady interest income compared to fee and trading income overall reduces the risk of banks. In line with expectations, the coefficient of *LIQ* is positive, indicating that larger liquidity buffers contribute to the stability of banks by insulating it better from shocks. The results for both the loan ratio (*LOANS*) and off balance sheet exposures (*OBS*) are statistically not significant, although the inclusion of these variables does improve the model as a whole. [18]

4.2. *Individual Effects of Interbank Activities*

Larger shares of both interbank lending and borrowing increase the risk of financial institutions as shown by negative coefficients of *exposurel* and *exposureb*, respectively (columns 1 through 4). This result contrasts the 'peer-monitoring' evidence reported in Dinger and von Hagen (2009) and supports the 'contagion' hypothesis. Put differently, banks operating in the Dutch interbank market do not appear to be better suited to assess risks of peers and mitigate risk by providing superior monitoring services.

[17] An alternative explanation could be mean reversion in returns on assets.
[18] Based on the the cross-sectional dependence (CD) test of Pesaran we cannot reject the null of independent cross-sectional disturbances at the 5% level. This is corroborated by the Friedman test. See De Hoyos and Sarafidis (2006) for details.

A potential reason for these deviating results could be, apart from the substantial difference of sampled Dutch versus EU-accessory state banks, the neglect of i) foreign players in domestic interbank markets and ii) the connectedness of Dutch banks in the interbank market in Dinger and von Hagen (2009). The former appears to be of lesser importance since in all four regressions, the coefficients of foreign lending ($foreignl$) and borrowing ($foreignb$) are not statistically different from zero. Contrary to van Lelyveld and Liedorp (2006), we can therefore not identify international counterparties as a prominent source of risk. An open banking system in general, and internationally integrated interbank markets in particular, are thus no threat to stability per se. Moreover, if we interact foreign lending and borrowing with bank type, we find that for bank type 4, higher foreign borrowing will even increase stability (results not shown).

Regarding the aspect of interconnectedness, a number of important differences across specifications 1 to 4 emerge. First, spill-over effects through interbank lending are consistently absent. Neither the coefficients of direct interbank-weighted risk of other banks in the system (wzl), nor those interacted with banking type in column 2 are significantly different from zero. Second, specification 3 shows that the effect of the borrowing risk of neighboring banks (wzb) is insignificant. But, controlling for the different bank types in specification 4, we see that the effect is significant for most types. If domestic peers are more stable, for both large (the coefficient of wzb is 2.02) or smaller banks (the coefficient of wzb is $2.02 - 1.86 = 0.16$), we find that higher connectivity in terms of borrowing on the interbank market enhances individual bank stability, too. In line with Dinger and von Hagen (2009), domestic peers therefore seem to be efficient monitors of each other. The negative net effect for foreign banks (wzb equal to $2.02 - 2.16 = -0.14$ for type 3 banks and $2.02 - 2.15 = -0.31$ for type 4 banks) in turn suggests that borrowing from banks with lower risk on the interbank market increases the riskiness of type 3 or 4 banks. Thus, in particular the funding of foreign banks through interbank markets is subject to a potential contagion channel.

4.3. Full model: Interbank Lending and Borrowing Activities Combined

Specifications 5 and 6 combine the effects of interbank lending and interbank borrowing, with and without banking type interaction effects, respectively. By and large, these complete models corroborate earlier findings. The direct effect of both interbank lending and borrowing is negative, meaning that banks with larger exposures of either kind on interbank markets are more risky. Foreign lending or borrowing likewise has no significant effect, providing evidence that open financial systems are not more risky per se. Regarding spill-over effects, we find again that that the risk of 'neighbors' in the banking system only affects individual banks' risk through funding exposures. Specification 6 highlights that in particular large Dutch banks benefit positively from borrowing exposures to more stable peers. For subsidiaries and branches, the effect is negative (the coefficient is $1.77 - 1.86 = -0.09$ for type 3 and $1.77 - 1.91 = -0.14$ for type 4 banks). Potentially, a less risky system invites and/or induces especially foreign banks to pursue riskier business models, funded among other sources by (stable) Dutch domestic banks, so as to gain a foothold in the Dutch banking market.

4.4. Core versus periphery counterparts

To investigate further how linkages between banks may amplify or weaken shocks to the system, we use a further breakdown of the interbank matrix by including the interaction frequency of banks. For each bank we determine the median number of contacts a bank has with it's counterparties. If a bank has above median number of contacts we consider these banks preferred counterparties and label them "core counterparties". The remaining, irregular counterparties we call "periphery banks". Once we have defined the core and periphery counterparts, we construct a new interbank matrix for core and for periphery counterparties. Note that these matrices may differ per bank and per activity (lending versus borrowing), but are stable over time. Combined with the z-score of these counterparties, and weighted by the size of the exposures, we now have four new variables (called *wcorezl*, *wperipheryzl* for core and periphery lending counterparties and *wcorezb* and *wperipheryzb* for core and periphery borrowing counterparties). Consider the results in Table 7. Column 1 shows the standard model, distinguishing between core and periphery counterparties in the case of interbank lending. In column 2 we check whether the results differ per bank type. Column 3 and 4 examine the impact for core and periphery counterparties for interbank borrowing and per bank type. Finally, column 5 and 6 show the results of the full model, i.e. for core and periphery banks for both interbank lending and borrowing and per bank type.

Table 7
Estimation results core-periphery model

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*wzl*	*wzl**type	*wzb*	*wzb**type	*wz*	*wz**type
size	−1.2969	−0.9344	3.4318	2.1803	−1.3124	−1.9223
	[7.8945]	[7.8157]	[7.9944]	[8.1672]	[7.9629]	[7.9528]
CAR	3.3961***	3.3959***	3.0088***	2.9929***	3.2462***	3.2191***
	[0.9284]	[0.9269]	[0.8232]	[0.8225]	[0.8687]	[0.8630]
GRWTH	−0.2578**	−0.2634**	−0.3121***	−0.3125***	−0.2729**	−0.2793**
	[0.1182]	[0.1178]	[0.1174]	[0.1176]	[0.1205]	[0.1200]
LLR	−24.9465**	−24.8126**	−26.8536***	−26.4915***	−27.0114***	−26.4643***
	[9.5852]	[9.5128]	[8.9366]	[9.2484]	[9.4468]	[9.7450]
MGT	−0.0469*	−0.0481*	−0.0509*	−0.0528*	−0.0472*	−0.0512*
	[0.0261]	[0.0255]	[0.0269]	[0.0271]	[0.0262]	[0.0260]
ROA	−7.7014*	−7.5899*	−9.5426**	−9.1010**	−7.9300**	−7.4871*
	[4.0878]	[4.0996]	[3.6972]	[3.7265]	[3.9307]	[3.9377]
II	0.2763**	0.2765**	0.2928***	0.2949***	0.2940***	0.2976***
	[0.1062]	[0.1059]	[0.1094]	[0.1072]	[0.1039]	[0.1009]
LIQ	2.3172***	2.3458***	2.5969***	2.5519***	2.4800***	2.4790***
	[0.7623]	[0.7548]	[0.7434]	[0.7391]	[0.7586]	[0.7492]
LOANS	−1.4287*	−1.4663*	−1.3436*	−1.2465	−1.3399*	−1.3048
	[0.7964]	[0.8048]	[0.8033]	[0.7772]	[0.8022]	[0.7974]
exposurel	−1.0027**	−0.9953**			−0.9937**	−0.9546**
	[0.4214]	[0.4183]			[0.4175]	[0.4185]
foreignl	−0.0293	−0.0348			0.0717	0.0594
	[0.1729]	[0.1739]			[0.2162]	[0.2167]
wzlcore	−0.0781	0.2165			−0.0761	0.1281
	[0.0583]	[0.2590]			[0.0586]	[0.2069]
wzlperiph	−0.0228	0.1754			−0.0217	−0.1587
	[0.0678]	[0.3014]			[0.0691]	[0.5468]
All type interactions with core and periphery variables included but not shown as they are all insignificant						
exposureb			−0.4838	−0.4589	−0.5039*	−0.5175*
			[0.2936]	[0.2957]	[0.2776]	[0.2882]
foreignb			−0.2756	−0.2300	−0.2397	−0.1974
			[0.1783]	[0.1838]	[0.2036]	[0.2012]
wzbcore			−0.0147	2.1042	−0.0130	1.7983
			[0.0801]	[2.4654]	[0.0799]	[2.6535]
wzbperiph			0.0711	0.5946***	0.0860	0.5956**
			[0.1406]	[0.2088]	[0.1413]	[0.2380]
type2xwzlcore				−1.9934		−1.6579
				[2.4700]		[2.6577]
type3xwzlcore				−2.4084		−2.0530
				[2.4764]		[2.6625]
type4xwzlcore				−2.2545		−1.9581
				[2.4611]		[2.6492]
type5xwzlcore				−1.4180		−1.1694
				[2.5109]		[2.7003]
type2xwzlperiph				−0.4041		−0.4247
				[0.4349]		[0.4548]
type3xwzlperiph				−0.6153***		−0.6022**
				[0.2171]		[0.2480]
type4xwzlperiph				−0.6104***		−0.5312**
				[0.2264]		[0.2467]
type5xwzlperiph				−0.6707**		−0.6699**
				[0.2641]		[0.2890]
Observations	3427	3427	3427	3427	3427	3427
R-squared	0.047	0.049	0.042	0.047	0.049	0.055
Number of inst	136	136	136	136	136	136

Robust standard errors in brackets, $***p < 0.01, **p < 0.05, *p < 0.1$.

Table 7 shows that the relevance of bank specific variables does not change, as expected. If we look at the new interbank variables, we find that for interbank lending, the distinction into core and periphery counterparties does not have a significant impact on bank stability. The same holds for core borrowing counterparties. However, for interbank borrowing we find that funding from stable periphery banks has a significant and positive effect on bank stability. This implies that borrowing from stable third parties contributes to the solvency of banks and hence to the well-functioning of the system. Potentially, such stable lenders are less prone to pre-emptive retreat from interbank markets on noisy signals, which causes system instability according to Huang and Ratnovski (2010). This effect is most prominent for the large banks and for the foreign branches. However, for foreign subsidiaries and investment firms, the option to borrow additional funds from third parties increase risk. This is in line with our earlier findings and may suggest that these banks will take on extra risks precisely because they are able to find funds on the interbank market if needed.

4.5. Bank-specific or system-specific risk determinants?

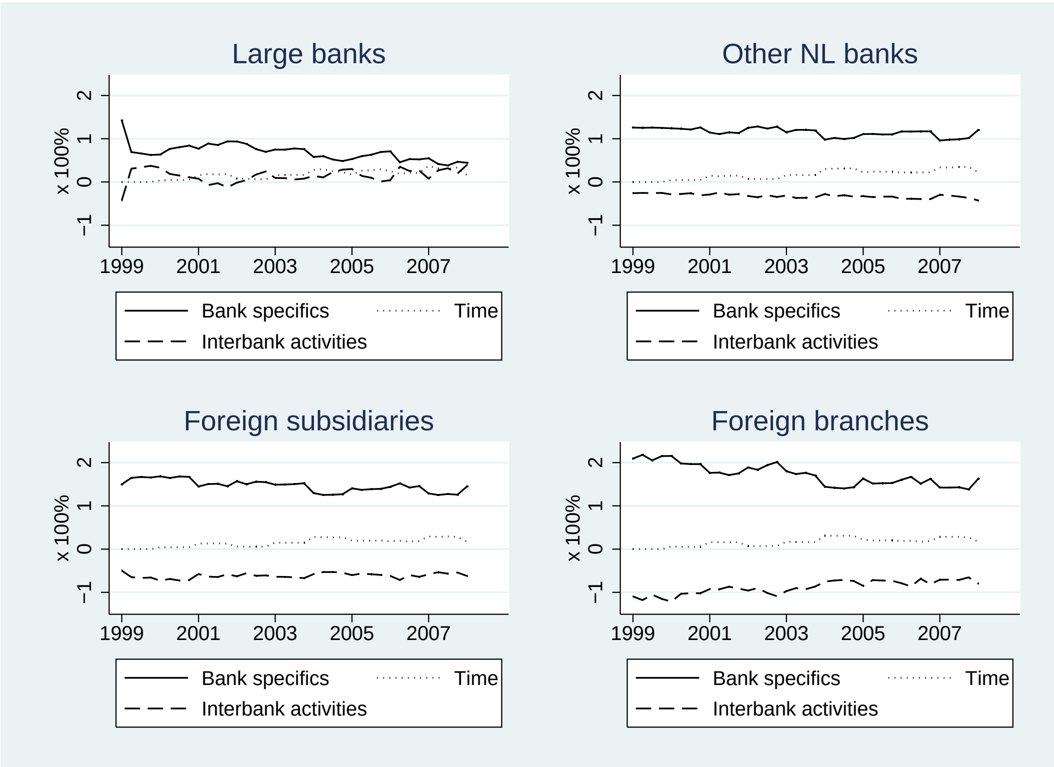
For policymakers it is crucial to understand the main drivers of individual bank's risk. If spill-over effects dominate the overall stability of banks, individual bank audits alone might for example fail to shed light on the economically most important contingencies against which supervisors and banks may want to insure. Therefore, we decompose predicted z-scores into three components: bank-specific, spill-over effects, and time effects. Given the estimated parameters in specification (6), in Table 6 we predict the z-score for each observation:

$$\hat{y}_{it} = \hat{\alpha}_i + x'_{it-1}\hat{\beta}_1 + z'_t\hat{\beta}_2 + q'_{it-1}\hat{\beta}_3,$$

where $\hat{y}_{it}$ is the predicted value of the z-score of bank i in period t, $\hat{\alpha}_i$ and $\hat{\beta}_k$, $k = 1,2,3$, represent the estimated values of the parameters. This predicted value can be decomposed into three parts: The term $x'_{it-1}\hat{\beta}_1$ represents the part of the predicted z-score due to the bank specific covariates. The second term, $z'_t\hat{\beta}_2$, is the part of the predicted z-score due to the year specific fixed effects. The last term, $q'_{it-1}\hat{\beta}_3$, is the part of the predicted z-score due to the interbank activities. This term reflects the overall effect of the interbank activities on the predicted z-score.

Figure 4 shows that for all bank types, the bank specific covariates explain the largest part of the predicted z-score. Hence, common supervisory practice to conduct on- and off-site audits of individual banks seems sensible since the dominant share of bank risk emanates from choices made by banks themselves in preceding periods. The absence of time-specific effects further corroborates the notion that bank-specific factors, rather than general macroeconomic circumstances, are prime drivers of bank risk.

Fig. 4. Decomposition of z-score



With the exception of large banks, interbank activities have a negative impact on the z-score. This is in line with our expectations and the 'contagion' hypothesis. For the large banks, the overall impact of the interbank activities, including both interbank lending and borrowing, as well as direct and indirect effects, is positive. Hence, our results highlight the crucial importance to take explicit account of the heterogeneity existing not only in the Dutch but many other developed banking systems. Support of the 'peer-monitoring' hypothesis for large banks may reflect that especially the dominant players in the interbank market monitor each other, and are monitored by other market participants, much more carefully compared to smaller, banks deemed perhaps less relevant.

5. Robustness Analysis

We conduct a number of robustness checks based on the full model specified in column (6) of Table 6. These tackle 1) common factors in bank risk, 2) sample heterogeneity, 3) bank origin, 4) endogenous participation decisions, 5) endogenous market risk and 6) market turmoil. We discuss each in turn. We find that in most robustness checks the main conclusions of the full model still hold. However, in a few robustness checks we find on the one hand that the direct effect of both interbank lending and borrowing is less significant and on the other hand, that the effect of $foreignb$ is significant.

First, we include the business cycle in a number of alternative ways since common macroeconomic shocks are often blamed as one possible source of sparking contagion in the financial system. Instead of including year dummies, we include quarterly dummies or GDP. Unreported results corroborate earlier reported findings that support the contagion hypothesis, but provide only limited evidence of spill-overs via funding in interbank markets.

Second, we estimate the full model for several subsamples to further explore sample heterogeneity. To examine whether the 'full-crisis' year 2008 drives our results, we exclude all quarters from that period. Next, we exclude investment firms, i.e. type 5 banks, since they provide markedly different financial services. As interbank assets and liabilities decrease systematically every fourth quarter, we include next an according dummy variable. Alternatively, we also estimate the model without the fourth quarter data. In all these cases, unreported results support the conclusions from the full model.

Third, we examine whether there is a difference between banks of Dutch origin and banks of foreign origin. Column (1) of Table 8 shows that both interbank lending and borrowing relative to total assets become less significant compared to the full model. In addition, we find a highly significant and negative effect of $foreingb$ for the subsample of Dutch banks. This means that risk increases if relatively more funds are borrowed from foreign banks compared to Dutch banks. For the foreign subsidiaries and branches, the impact does not change however. Next, we focus on the subsample of type 1, 2 and 3 banks, since DNB plays no role in solvency supervision of foreign branches (type 4 banks). Column (2) shows that *exposureb* is not significant for this subsample. However, the relative size of borrowing from foreign banks becomes significant, indicating that if the relative share of foreign borrowing increases, risks increase as well.

Table 8
Robustness analysis

	(1)	(2)	(3)
VARIABLES	Type 1 and 2	Type 1, 2 and 3	Exit and entry
size	1.8734	4.3486	0.2447
	[20.7496]	[11.6190]	[15.8414]
CAP	3.9965***	4.3045***	5.3384***
	[1.1682]	[1.1059]	[1.5266]
GRWTH	−0.6823**	−0.4967**	−0.1870
	[0.3207]	[0.2303]	[0.1793]
LLR	0.3453	−1.0627	−1.5732*
	[1.3763]	[0.9625]	[0.8917]
MGT	−0.2045***	−0.1524***	−0.0795**
	[0.0505]	[0.0497]	[0.0357]
ROA	−5.5142	−8.8792*	−8.9691**
	[5.6018]	[4.5993]	[4.0680]
II	0.4296**	0.4061***	0.2322*
	[0.1706]	[0.1381]	[0.1226]
LIQ	3.7136***	3.5927***	3.5377***
	[0.9517]	[0.8292]	[1.1288]
LOANS	1.1895	0.1069	0.7103
	[0.9381]	[0.7714]	[0.5043]
OBS	−0.0224	0.0350	−0.1073*
	[0.1915]	[0.1424]	[0.0559]
exposurel	−0.6900	−1.3729**	−0.5967
	[0.7756]	[0.6552]	[0.4066]
foreignl	0.2066	0.0975	0.1165
	[0.3845]	[0.2360]	[0.2282]
wzl	0.2735	0.2247	0.1259
	[0.1845]	[0.1717]	[0.1792]
$type2 \times wzl$	−0.3247	−0.2903	−0.2553
	[0.2043]	[0.1920]	[0.2024]
$type3 \times wzl$		−0.3121	−0.0861
		[0.2021]	[0.1920]
$type4 \times wzl$			−0.1562
			[0.2275]
$type5 \times wzl$			−0.2022
			[0.1960]

Table 8
Robustness analysis (continued)

	(1)	(2)	(3)
VARIABLES	Type 1 and 2	Type 1, 2 and 3	Exit and entry
exposureb	−0.7517	−0.2810	−0.3306
	[0.7920]	[0.5080]	[0.3390]
foreignb	−0.5506*	−0.3059	−0.1188
	[0.2902]	[0.2310]	[0.2228]
wzb	1.5798	1.6470	1.7702*
	[1.0340]	[1.0767]	[1.0295]
$type2 \times wzb$	−1.4935	−1.4872	−1.3063
	[1.0421]	[1.0837]	[1.0648]
$type3 \times wzb$		−1.7405	−1.9155*
		[1.0755]	[1.0385]
$type4 \times wzb$			−1.8991*
			[1.0285]
$type5 \times wzb$			−1.9565*
			[1.0506]
Constant	−179.7668	−158.7670	−210.8180
	[302.6581]	[181.4243]	[231.9429]
Observations	1362	2278	1818
R-squared	0.072	0.055	0.092
Number of inst	52	90	50

Robust standard errors in brackets, $***p < 0.01, **p < 0.05, *p < 0.1$
Types 1 through 3 are Large banks, Other NL banks, and Foreign subsidiaries, respectively.

Fourth, participation in the Dutch interbank market might be endogenous, e.g. risky parties may no longer receive credit from peers, or banks may depart the market in the wake of consolidation, and therefore not show up in the data. We control for exit and entry of banks on the Dutch interbank market and consider only the subsample of banks which are present on the Dutch interbank market in each sample period, i.e. a subsample of 50 banks. Column (3) shows that the direct effect of interbank lending and interbank borrowing turns insignificant. The effect of the weighted riskiness of all banks from which a bank borrows is still similar to the full model estimated on the full sample. So for types 1 and 2 the effect is positive, i.e. borrowing from a less risky environment makes a bank less risky. Bank types 3 and 4 become more risky when they borrow from a less risky environment.

Fifth, the variables that measure the sensitivity to the risk of neighboring banks, (*wzl* and *wzb*), are both weighted averages of all banks *z*-scores. Therefore *wzl* and *wzb* may be endogenous with respect to bank risk. We use an instrumental variables approach to check for this. As instruments for *wzl* and *wzb* we use lagged values of these variables. The main conclusions of our full model still hold. The null hypothesis that all specified endogenous variables can be treated as exogenous cannot be rejected. Therefore we conclude that *wzl* and *wzb* can be treated as exogenous. The same holds for our measure of return (*ROA*) and leverage (*CAP*). Here we tested for endogeneity as well, we ran the model without *ROA* and separately also without *CAP*, and used an alternative return measure (*ROE*) in the case of *ROA* and an alternative calculation of leverage (reserves as a percentage of total assets). Overall, the tests and the alternative specifications do not change the baseline model.

Finally, we checked whether our results are robust to periods of stress. We include the volatility of the Euribor 1 week rate and an interaction of the volatility with our main variables of interest, *wzl* and *wzb*. In no case are these significant. [19]

6. Conclusion

We test two competing hypotheses on the relation between interbank market activity and bank risk: the 'peer-monitoring' and the 'contagion' hypothesis, respec-

[19] As an alternative measure we included the difference between the interest rates on interbank loans and short-term U.S. government debt (TED spread) with the same results.

tively. The former conjectures that bankers are better monitors and are therefore particularly well-suited to discipline peers. Higher interbank exposures should thus lead to a safer risk profile, all else equal. The latter argues that intensive connectivity in interbank markets can facilitate the propagation of problems at individual banks throughout the system. Banks' risk should thus rise as interbank exposure increases.

Using detailed quarterly data provided by the Dutch central bank DNB on both interbank borrowing and lending exposures, we control for conventional risk-drivers and employ a simple spatial lag model to separate the effect of i) larger lending (borrowing) shares in interbank markets, ii) larger international exposures, and iii) possible spill-overs from lending to (borrowing from) more stable counterparties. Our main findings are threefold.

First, both larger lending and borrowing shares in interbank markets increase the riskiness of banks active in the Dutch banking market. This result supports the 'contagion' hypothesis and is robust to the separate or simultaneous specification of proxies for lending and borrowing activities in interbank markets.

Second, we find no significant relation between the risk of other banks in a bank's *lending* network and individual bank risk. This implies that the riskiness of the banks to which a bank lends has no bearing on bank's risk. Hence, interbank lending appears to be of much lesser importance to explain the propagation of (credit) risks through the banking system. In fact, we find instead a significant relation between the weighted risk of all banks from which a bank *borrows* and individual bank risk. Borrowing intensively from more stable banks also has positive spill-overs for the average individual institution. Likewise, this points to the importance of interbank funding networks since deteriorating stability of counterparties would then also entail possible negative spill-overs. Banks benefit especially from the possibility to borrow funds irregularly from banks with which they do not often do business. A flexible interbank market does contributes to the stability of the system.

Third, these effects differ significantly across banking groups and emphasize the need for a sufficiently nuanced picture. Specifically, while we do not find any evidence that in particular foreign lending or borrowing has a relation to risk, the positive spill-overs in interbank markets are confined to domestic Dutch banks.

Foreign banks active in the Dutch interbank market, in turn, exhibit a negative interbank spill-over relation such that borrowing from stable banks actually reduces their stability.

A. Entropy maximization and cross entropy minimization

A.1. *Entropy maximization*

We build on a matrix M_t as discussed in paragraph 2 of the main text. Assume that the matrix M_t is normalised such that $\sum_{i=1}^{n_t+1} a_{t,i} = \sum_{j=1}^{n_t+1} l_{t,j} = 1$. Now $m_{t,ij}$ can be interpreted as the share of the total exposure that goes from i towards j. The entropy of the distribution of probabilities is now given by $-\sum_{i=1}^{n_t+1}\sum_{j=1}^{n_t+1} m_{t,ij}\ln m_{t,ij}$. Now we add the restrictions and obtain the following problem to be solved:

$$
\begin{aligned}
\min \sum_{i=1}^{n_t+1}\sum_{j=1}^{n_t+1} & m_{t,ij}\ln m_{t,ij} \\
\text{subject to} \sum_{j=1}^{n_t+1} & m_{t,ij} = a_{t,i} \\
\sum_{i=1}^{n_t+1} & m_{t,ij} = l_{t,j} \\
& m_{t,ij} \geq 0.
\end{aligned}
\tag{A.1}
$$

Wells (2004) shows that when no further additional information is used to solve this problem, the solution is given by $m_{t,ij} = a_{t,i} \times l_{t,j}$. This solution means that lending of bank i towards bank j is increasing in both bank i's total lending and bank j's total borrowing.

There are two things worth noting about the solution. First if bank i is both a lender and a borrower the solution will yield $m_{t,ii} > 0$. This means that bank i will lend to itself. Second, the solution does not take into account that a bank might prefer certain counterparties over others. To take these two issues into account we define a prior on M_t. Then the objective is to find the distribution that satisfies the constraints and is as closest as possible to our prior. This means that we minimize the cross entropy. Cross entropy minimization is a commonly used approach for similar problems, see for example Upper and Worms (2004), Wells (2004), Degryse and Nguyen (2007) and van Lelyveld and Liedorp (2006).

van Lelyveld and Liedorp (2006) compared the interbank lending matrix for the

Dutch market estimated using large exposures data to the matrix estimated using direct information for a large part of the market. Their study showed that the entropy estimation using large exposures is a good approximation for the distribution of the actual linkages. Therefore we use the distribution of the large exposures data to define our prior on M_t.

Let E_t be the matrix with the large exposures data. For $i, j = 1, \ldots, n_t$, $E_{t,ij}$ represents the exposure of bank i towards bank j as reported in the large exposures data. There are two problems with the large exposures data. The first is that some banks report outstandings while others report limits in the large exposures data. Using E_t directly to determine M_t^0 may bias towards banks that report limits since limits are larger than outstandings. Therefore we first convert the matrix E_t to percentages of each bank's total exposures (that is, either total outstandings or total limits). Let $\tilde{E}_t$ denote the matrix with percentages, i.e. $\tilde{E}_{t,ij} = \frac{E_{t,ij}}{\sum_{j=1}^{n_t+1} E_{t,ij}} \times 100$, $i = 1, \ldots, n_t$, $j = 1, \ldots, n_t + 1$. So $\tilde{E}_{t,ij}$ represents the exposure of bank i towards j expressed as a percentage of bank i's total exposure.

The second problem with the large exposures data is that $E_{t,(n_t+1)j}$ is unknown. That is, the exposures of foreign banks towards bank j are unknown. Therefore we cannot determine $\tilde{E}_{t,(n_t+1)j}$ directly, but deduct them from the ratio of foreign interbank lending to total lending. Note that some $E_{t,ij}$'s can be zero, since then there is no large exposure from bank i towards bank j. However for computational ease we replace these elements by a very small number in the estimation. These small numbers can be interpreted as reflecting the many small interlinkages that most banks have but fall below the threshold value for reporting large exposures.

Now all the elements of the matrix $\tilde{E}_t$ are known. To determine M_t^0, the prior for the distribution, the diagonal elements of $\tilde{E}$ are set to 0 ($\tilde{E}_{t,ii} = 0$). Next, to obtain M_t^0, the matrix $\tilde{E}$ is normalized, so elements of M_t^0 are given by $M_{t,ij}^0 = \frac{\tilde{E}_{t,ij}}{\sum_{i=1}^{n_t+1} \sum_{j=1}^{n_t+1} \tilde{E}_{t,ij}}$. The problem formulated in (A.1) can now be reformulated as follows:

$$
\begin{aligned}
\min \sum_{i=1}^{n_t+1} \sum_{j=1}^{n_t+1} m_{t,ij} \ln \frac{m_{t,ij}}{m_{t,ij}^0} \\
\text{subject to} \sum_{j=1}^{n_t+1} m_{t,ij} = a_{t,i} \\
\sum_{i=1}^{n_t+1} m_{t,ij} = l_{t,j} \\
m_{t,ij} \geq 0.
\end{aligned}
\tag{A.2}
$$

The problem can be solved by the RAS algorithm. The algorithm is an iterative procedure that iteratively uses column and row constraints. The starting values are given by the matrix M_t^0. Iteration $s+1$ is given by (see Blien and Graef (1997))

$$
\begin{aligned}
m_{t,ij}^{s+1} &= \frac{m_{t,ij}^s a_{t,j}}{\sum_i m_{t,ij}^s}, \text{ for column constraints and} \\
m_{t,ij}^{s+1} &= \frac{m_{t,ij}^s l_{t,i}}{\sum_j m_{t,ij}^s}, \text{ for row constraints.}
\end{aligned}
$$

With multiple iterations, we ultimately find M_t^*.

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