Contagiousness and Vulnerability in the Austrian Interbank Market

Claus Puhr,
Reinhardt Seliger,
Michael Sigmund[1]

The purpose of this paper is to analyze (hypothetical) contagious bank defaults, i.e. defaults not caused by the fundamental weakness of a given bank but triggered by failures in the banking system. As failing banks become unable to honor their commitments on the interbank market, they may cause other banks to default, which may in turn push even more banks over the edge in so-called default cascades. In our paper we distinguish between contagiousness (the share of total banking assets represented by those banks that a specific bank brings down by contagion) and vulnerability (the number of banks by which a bank is brought down by cascading failures).

Our analysis consists of three steps: first, we analyze the structure of the Austrian interbank market from end-2008 to end-2011. Second, we run (hypothetical) default simulations based on Eisenberg and Noe (2001) for the same set of banks. Finally, we estimate a panel data model to explain the (hypothetical) defaults generated by these simulations with the underlying structure of the network using network indicators that reflect (i) the network as a whole, (ii) a subnetwork or cluster, and (iii) the node level based on banks' interbank lending relationships. As a result we find strong correlations between a bank's position in the Austrian interbank market and its likelihood of either causing contagion or being affected by contagion.

Although our analysis is based on a dataset constrained to the interbank market of unconsolidated Austrian banks, we believe our findings could be verified by analyzing other banking systems (albeit with a different model calibration). Given the importance of identifying systemically important banks for the formulation of macroprudential policy, we believe that our analysis has the potential to improve our assessment with regard to second-round effects and default cascades in the interbank market.

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1 Introduction

1.1 Motivation

The financial crisis has revealed the danger of systemic risk due to contagion effects given the interconnectedness of modern banking systems. Identifying systemically important banks has since become one of the key objectives of systemic risk assessment and a necessary precondition for the formulation of macroprudential policy. Systemically important banks can be identified in many different ways. We would like to contribute to this important discussion by applying techniques from network economics.

In general, network analysis requires two input arguments. First, it takes a network, which could either be given or derived through a network formation process. Second, each network analysis needs an objective. In our paper we consider the interbank lending network as given and leave the theory on network formation aside, since the Austrian interbank lending relationships are the

[1] *Oesterreichische Nationalbank, Financial Markets Analysis and Surveillance Division, Claus.Puhr@oenb.at, Reinhardt.Seliger@oenb.at (corresponding author), Michael.Sigmund@oenb.at. This paper is a reader-friendly version of "Novel Ideas to Explain Active and Passive Contagion – Adding (More) Structure to the 'Banking-System-as-Network' Debate" by the same authors. We would like to thank Michael Boss, Helmut Elsinger, Gerald Krenn, Stefan W. Schmitz and Martin Summer (all OeNB) for the tools put at our disposal as well as the inspiration provided and Sam Langfield for his helpful comments. The views expressed in this paper are those of the authors and do not necessarily reflect those of the OeNB or the Eurosystem.*

very network we supervise.[2] We view the interbank lending market as a network where each participating bank is a *node* and each credit a *link*.

The objective of our paper is analyzing one important contagion mechanism within this network, namely counterparty credit risk associated with interbank lending. Ex ante it is unknown whether difficulties at even a relatively small (but interconnected) institution might trigger problems at another bank. In the context of macroprudential analysis such an institution could be considered as a systemically important bank (also known as a key player in network economics). Specifically, we analyze two variants of (hypothetical) contagious default for the Austrian network of interbank lending relationships. First, we study a bank's *contagiousness* in terms of the share of total banking assets represented by other banks that it will cause to default given its own default. Second we study a bank's *vulnerability* in terms of the number of banks by which it is brought down if defaults cascade through the banking sector.

In the remainder of the paper we try to identify key network properties that influence our two variants of contagious default. Our main motivation is finding out whether simulated *contagiousness* and *vulnerability* is driven by (i) banks' idiosyncratic characteristics (i.e. a thin capital buffer) or (ii) network effects/positions, or (iii) by both.

To this end we estimate panel data models that exploit network indicators to predict potential default cascades following individual bank failures while we control for idiosyncratic variables (i.e. the traditional measures of risk-bearing capacity like capitalization ratios etc.). If supervisors are able to identify network indicators that add significantly to the analysis of these models, macroprudential policy will be able to (i) analyze the characteristics/drivers of individual indicators to get a better understanding of default dynamics and (ii) potentially target selected variables to address *contagiousness* and *vulnerability* in the interbank market "indirectly." Our results should therefore provide potential novel means for policymakers to design and/or complement macroprudential tools.

1.2 Related Literature

To the best of our knowledge we are the first to apply panel estimation techniques to interbank liability networks to explain simulated contagious defaults by peer effects for a dynamically developing network over time. The analysis of network effects is not new to other economics fields. Particularly relevant for our paper is the work that followed Furfine's (1999a and 1999b) seminal contribution in which he tried to address the shortage of bilateral exposure data by extracting such information from transaction data. Based on his algorithm, payment system researchers, in particular a community around the Bank of Finland, started to analyze interbank lending exposures.[3] Soramäki et al. (2007), who also applied techniques from the social sciences and physics, were another important inspiration for our work.[4] Recently, there has been a significant interest in directly reported bilateral exposure data as well as

[2] *Moreover, shaping interbank lending relationships in a risk-optimal fashion while capturing all the strategic details is still in its academic infancy. See Cohen-Cole et al. (2010) for a first promising attempt.*

[3] *For an overview of their work see Leinonen (2007 and 2009).*

[4] *They analyze payments transferred between U.S. commercial banks over the Fedwire Funds Service.*

data extracted from payment systems data.[5]

In financial network studies, the closest work from a methodological perspective is Schmitz and Puhr's (2009) investigation of structure and stability for the Austrian large value real-time gross settlement system ARTIS. In this paper the authors also used panel data analysis to test the predictive power of structure for liquidity shortages in the event of (hypothetical) operational outages. With regard to interbank lending, the two closest related articles are on the Austrian and German interbank market. The Austrian interbank lending market has been investigated by Boss et al. (2004), and we draw on a similar dataset as well as from the inspiration of their seminal work. The German interbank market has been analyzed by Upper and Worms (2004). They show that the risk – notwithstanding the shortcoming of all aforementioned papers including our own work that suffers from a rather mechanical integration of the interbank lending channels – is material enough so that the failure of a single bank could lead to the failure of up to 15% of the entire banking system in terms of total assets. Beyond the OeNB's Systemic Risk Monitor (SRM) it seems appropriate to mention the Bank of England's RAMSI[6] that also includes the Eisenberg and Noe (2001) network model.

The remainder of the paper is structured as follows: section 2 covers our data source, section 3 the tools and methodologies employed. In section 4 we present our results before we conclude in section 5.

2 Data[7]

Our main data source is Austria's central credit registry, which covers individual credit risk-sensitive instruments with a volume of more than EUR 350,000 for each Austrian bank on an unconsolidated level on a customer-by-customer basis. Data available from the registry include the outstanding volume of securitized and nonsecuritized loans, guarantees and commitments as well as respective collaterals, specific provisions and the internal rating of the customers' credit quality. Moreover, the data source also covers interbank loans, the focus of our investigation, with the limitation that short-term interbank transactions (with a maturity of less than a month) have been subject to reporting requirements only since 2008. Hence, we are constrained in our analysis to quarterly observations from December 2008 to December 2011.[8] While exposures are reported on a monthly basis, we use additional data sources for the hypothetical default simulations, i.e. the capital positions of each bank at each point in time, which are available on a quarterly basis only. Finally, it is important to point out that our panel data set is balanced.[9]

3 Methodology

The following section is divided into three subsections. First, we explain our use of network indicators with a particular focus on their usability for financial systems/lending relationships amongst banks. Second, we describe briefly the tools/methodology employed to run hypothetical default simulations.

5 *See for example Cont et al. (2010) or Jaramillo et al. (2012).*

6 *For a description of RAMSI refer to Alessandri et al. (2009).*

7 *For a detailed description of the data see Boss et al. (2006a).*

8 *Given the reporting threshold of EUR 350,000, we are confident to cover the entire interbank market.*

9 *No default simulation results are available for Q2 2010, instead of 13 we have to contend with 12 observations.*

Third and finally, we describe the panel data regression techniques used to analyze the potential predictive power of structural patterns (i.e. network indicators) for stability (i.e. simulated contagious defaults).

3.1 Network Indicators[10]

We calculated approximately 100 different candidate network indicators for analysis. However, in the following section we describe a noteworthy subsample which at a later stage is either (i) used to describe the Austrian interbank market as a network (see section 4.1) or (ii) used to explain contagion via structural indicators (4.3).

Degree

The *degree* k_h of node h is measured by the number of *links* originating *(outdegree)* or terminating *(indegree)* at *node h*. *In-* and *outdegree* will match each other in an undirected network. For the interbank liability network, these *links* reflect the number of loans granted *(outdegree)* or received *(indegree)*. A high degree therefore indicates that an institution is very active in the interbank market. Traditional network analysis – within and outside the scope of financial systems – has often focused on degree distribution, because many real-life networks show properties far from what could be expected from random networks.[11]

Density

The connectivity of *node h* is its *degree* over the number of *nodes n*. On a network level, *average connectivity,* or *density,* is defined by the number of actual (directed) *links m* over the number of possible (directed) *links n(n–1)*. For the interbank liability network, a high *density* therefore reflects a very active interbank market with many lending relationships amongst participants.

Betweenness centrality

The *betweenness centrality* $C_B(h)$ of *node h* provides a measure of how many *shortest paths* d_{ij} pass through node h. Let $s_{ij}^{(h)}$ be the number of *shortest paths* between all pairs of *nodes i,j* that pass through the *node h*, and let s_{ij} be the number of all *shortest paths* between all pairs of *nodes i,j* then:

$$C_B(h) = \sum_{h \neq i \neq j} \frac{s_{ij(h)}}{s_{ij}}$$

In the context of the interbank liability network, *betweenness centrality* provides a measure of centrality in the sense that many of the shortest paths contain only central *nodes*. As the likelihood of centrality increases with the number of interbank relations, we expect larger, more important – in a systemic sense – institutions to rank high. This should be particularly true for a tiered banking system, where often the only "entry point" of the shortest paths to a cluster runs through the apex institution of that very cluster (comparable to a traditional hub-and-spoke structure).

Katz (status) centrality[12]

For our purposes the Katz centrality of a bank describes how important a bank is by relating it to the importance of other banks from which it borrows. The method is self-referential and also takes into account different *link*

[10] *Where possible we follow the notation of Albert and Barabási (2002).*

[11] *See for example Dorogovtsev et al. (2000) and Albert and Barabási (2002).*

[12] *See Katz (1953).*

strength (i.e. loan size). It is formally defined as

$$C_{Katz}(i) = \sum_{k=1}^{\infty} \sum_{j=1}^{\infty} \alpha^k (A^k)_{ji}$$

where A stands for the adjacency matrix and α[13] for attenuation factor. Of all centrality measures it is our preferred indicator in an interbank network context (see section 4.3.1 for a detailed discussion).

Clustering coefficient

The *clustering coefficient* $C_c(h)$ of an individual *node* h with k_h neighbors measures how well the latter are connected among each other.[14] The number of potential *links* between the k_h neighbors is $k_h(k_h - 1)/2$. Let the actual number of nodes between them be E_h so that:

$$C_C = \frac{E_h}{k_h(k_h - 1)/2} .$$

For the interbank liability network, the *clustering coefficient* provides a measure of connectedness of the neighboring banks; i.e. neighboring banks that share mutual relations are more likely to share the burden of a potential default and are at the same time more likely to suffer from contagion.

Clustering

Clustering – as opposed to the *clustering coefficient* – is not a network indicator but used to identify community structures within a given network with the aim to find members that "belong together." This can be achieved by various methods. The one employed in this paper builds on optimizing *modularity,* where, for a given division of the network's *nodes, modularity* reflects a high concentration of *links* between a cluster's *nodes* compared to a random distribution of *links* between all *nodes* regardless of clusters.[15] With regard to interbank liability matrices in general, and those of tiered banking systems in particular, cluster analysis aims to address/analyze the historically established structure of a banking system.

K-cores

K-cores are another means of identifying community structures within a given network, in this case communities of "importance." A *k-core* is a subnetwork of a given network where each *node* has at least a value of k in the respective property under investigation (usually a *degree* of k).[16] In the context of interbank networks, this allows to sample the core of the network, i.e. the highly connected institutions according to a defined threshold.[17]

3.2 Default Simulations

The following section explains the tools/methodology employed to run a hypothetical default algorithm to simulate hypothetical contagion effects within the Austrian banking system. To generate the underlying data, we used the OeNB's Systemic Risk Monitor (SRM).[18] One of the key assets of the SRM is that it links, amongst

[13] *This factor has been set to 1/(1+min(max(indegree, outdegree)) to ensure convergence of the infinite series.*

[14] *See Watts and Strogatz (1998).*

[15] *See Newman et al. (2006).*

[16] *See Seidman (1983) and Batagelj and Zaveršnik (2002).*

[17] *An illustrative example is included in chapter 4.3.1.*

[18] *See Boss et al. (2006a and 2006b).*

others, Austria's central credit registry data (described in section 2) with more traditional supervisory reporting data (e.g. capital positions), thus providing an integrated view of various data sources and different risk categories. The SRM model also includes an assessment of contagion risk through the interbank market.

In greater detail, the data generated by the SRM comprise a set of $N = \{1,...,n\}$ banks. Each bank is characterized by an exogenously given value of equity e_i net of interbank positions, and the network is represented as an $n \times n$ nominal liability matrix L, where L_{ij} stands for the liability of bank i to bank j.[19] Each interbank lending network is thus a pair (L,e).[20] The SRM also runs Elsinger et al.'s (2006) implementation of the Eisenberg Noe (2001) hypothetical network clearing algorithm and the hypothetical default simulations for each bank at each quarter. Using this algorithm we construct the dependent variables of our analysis.

First, we look at *contagiousness,* calculating for each time period t and for each bank i in our sample the number of banks that are brought down by a *fundamental default* of bank i. Second, the *vulnerability* of bank i reflects the number of banks (relative to its *outdegree*)[21] whose *fundamental default* induces bank i to default as well. In our context a *fundamental default* means that a bank cannot repay any of its obligations.[22] Except for the initial exogenous default, all other induced defaults need not be fundamental. We assume an *induced default,* i.e. one that occurs due to contagion, if the *capital adequacy ratio* (CAR) falls below 2%.

The hypothetical default algorithm has the following structure. For each period t and each bank i we assume a *fundamental default* to happen, subject to the assumption that all other payments are served. If no other bank defaults in turn, then the algorithm is terminated. However, if another bank defaults as well then the algorithm proceeds, subject to the adjusted assumption that all liabilities are served proportionally.[23] Subsequently, the algorithm either stops if no new defaults occur or triggers a new clearing round if further defaults cause other banks to fail to meet some of their liabilities. The algorithm stops after n rounds at the most. Thus, the resulting *contagiousness* of bank i at period t reflects the number of sequential defaults of the clearing algorithm, whereas the *vulnerability* of bank i is the result of all n-clearing algorithm sequences for each bank j for period t; i.e. it simply counts the number of sequential defaults of bank i.

[19] *For economic and technical reasons we assume that $L_{ij} \geq 0$ and $L_{ii} = 0$. This means that nominal liabilities are defined to be positive without loss of generality and that a bank cannot lend to itself. Intragroup transactions are not excluded since we look at unconsolidated Austrian banks.*

[20] *The conceptual framework of the interbank market network model is based on Elsinger et al. (2006). It is an extended version of the network model of Eisenberg and Noe (2001). We refer to these papers for a more detailed description of a financial network.*

[21] *A bank can be vulnerable to the default of more banks than its outdegree, i.e. immediate neighbors, so this procedure can be understood as a proportional normalization.*

[22] *In general different degrees of exogenous defaults could be analyzed. A fundamental default is the most extreme but straightforward assumption as any kind of proportional repayment of liabilities would create room for additional interpretation.*

[23] *It is possible to include levels of seniority into the liability structure as well.*

3.3 Panel Data Regressions

In this section we outline the econometric theory and estimation procedure behind the models to explain *contagiousness and vulnerability*. Considering the structure of the data (banks, time periods) we choose a panel model approach to link the dependent variables to independent (network and balance sheet) indicators. For both dependent variables we follow a standard test procedure to select the statistically best model. We consider the following model:[24]

$$y_{i,t} = \alpha_i + x^T_{i,t}\beta + u_{i,t}$$

where y represents the endogenous variables and x the exogenous variables. We assume the same slope coefficients of the independent variables ($\beta_i = \beta$) as we do not observe enough time periods to produce efficiently estimated coefficients. Following the standard literature on static panel econometrics we are left with two options concerning α_i: fixed effects or random effects. In contrast to a fixed effects model the random effects model implies $E[\alpha_i x_{i,t}] = 0$. So there is no correlation between the individual specific effect and all other independent variables. A Hausman test is used for each panel model in section 4.3 to find the most appropriate model.[25]

4 Results[26]

4.1 Structure: The Austrian Interbank Market as a Network

A lot has been written about interbank lending relationships. To the best of our knowledge, however, all authors who have come before us[27] have disregarded stable structural features in their attempt to describe the banking system with network indicators. We will proceed likewise in subsection 4.1.1, but aim to add to this analysis in subsection 4.1.2 by discussing empirically identified clusters in our dataset and relating them to the historically established structure of the Austrian banking system.

4.1.1 Network Properties

In this subsection we use our balanced panel of 749 banks, for which we have quarterly observations from end-2008 to end-2011.[28] We will discuss averages and distributions of the network indicators presented in section 2.1.

Based on one of the most prominent network indicators, *degree,* we can already establish one of the main features of the Austrian interbank network that has its origin in the historically grown Austrian banking system: a few important central *nodes* and many smaller banks; i.e. the tiered structure of the Austrian banking system, due to the importance of the savings and cooperative banking sectors,[29] is reflected in

[24] *Given a set of independent variables we test whether the data can be pooled. Usually the poolability hypothesis is strongly rejected as panel data allow to control for time-invariant variables that cannot be observed or measured. In the context of finance these could be time invariant bank-specific characteristics such as the underlying business model.*

[25] *In the presence of heteroskedasticity we use robust standard errors in the various panel estimations. Therefore we need to use a more general Hausman-type test to choose between fixed and random effect models. See Arellano (1993) for more details and Schaffer and Stillman (2006) for a STATA software implementation.*

[26] *Networks in this chapter were visualized using Pajek and Visone.*

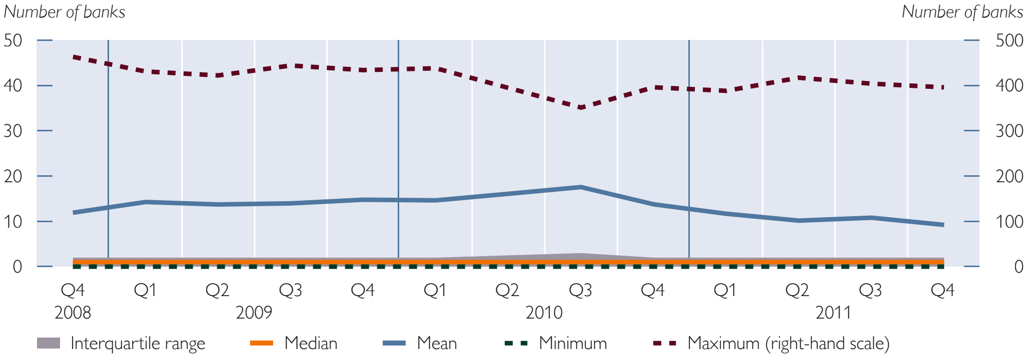
[27] *From Boss et al. and Upper and Worms (both 2004) to Cont et al. (2010) and Jaramillio et al. (2012).*

[28] *With the exception of Q2 2010, where no data are available.*

[29] *In Austria we have got one savings bank sector ("Sparkassen") and two cooperative banking sectors ("Raiffeisen" and "Volksbanken").*

Chart 1

Interquartile Ranges: Outdegree

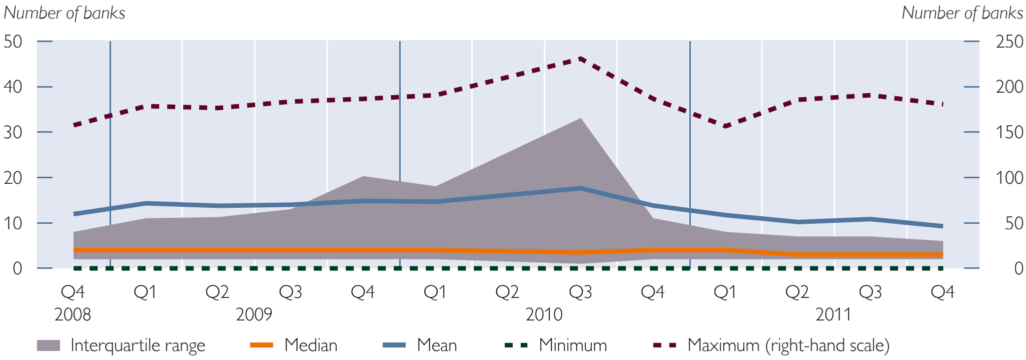


Source: OeNB calculations.

Note: The results are based on a sample of 749 Austrian banks from end-2008 to end-2011 (with the exception of Q2 2010 for which no data were available).

Chart 2

Interquartile Ranges: Indegree



Source: OeNB calculations.

Note: The results are based on a sample of 749 Austrian banks from end-2008 to end-2011 (with the exception of Q2 2010 for which no data were available).

the distribution of *outdegrees* (see chart 1) and *indegrees* (see chart 2).[30]

Both charts show the mean and interquartile ranges, with the mean most of the time above the 3rd quartile.[31] Interestingly enough, the "lender"-indicator *outdegree* is significantly more concentrated than the "borrower"-indicator *indegree*. Moreover, although the maximum in both cases is off the scale, it is on average above 400 for the former and less than 200 for the latter.[32] Finally, a look at the development over time reveals that the mean *degree* (both *out*- and *indegree*) as well as the two middle quartiles de-

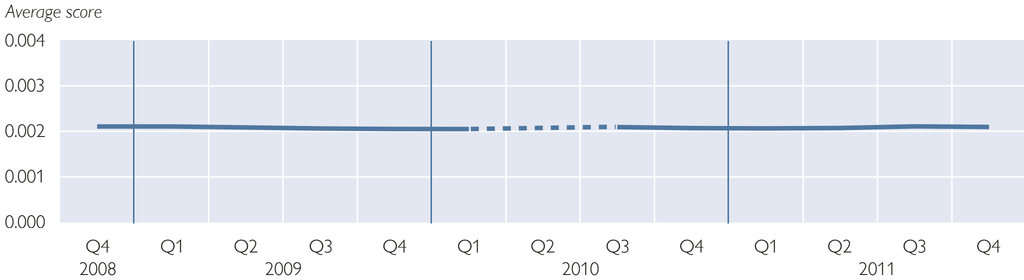
[30] *Although not unrelated, it is not only about the size of these institutions.*

[31] *The mean out- and indegree is by definition the same for each point in time. By design, important structural information is hidden.*

[32] *The minimum for both, at each point in time, is 0. Not necessarily by definition, but also not unexpected, given the number and size of banks in our sample.*

Chart 3

Average Betweenness Centrality

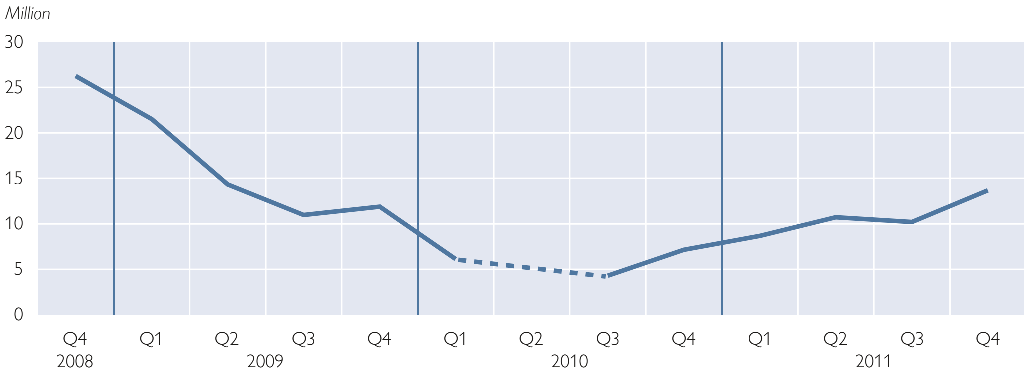


Source: OeNB calculations.

Note: The results are based on a sample of 749 Austrian banks from end-2008 to end-2011 (with the exception of Q2 2010 for which no data were available).

Chart 4

Variance of Katz Centrality[1]



Source: OeNB calculations.

[1] The absolute level of the variance is in millions but has no real significance.

crease from end-2008 to end-2011. This reveals a reduction in interbank connections of our sample, or – put in different terms – reduced density of the network.

The average *betweenness centrality* remains almost completely stable over time (see chart 3). This might be associated with stable structural properties of the Austrian banking systems that can be observed independently of the network *density,* which has fluctuated between end-2008 and end-2011. However, looking at the variance of the weighted *Katz centrality* (see chart 4), which can be interpreted as a weighted network concentration measure (note the inverse trend compared to mean *in-* or *outdegree*), we conclude that the network, after having taken a path towards greater diversification, is now exhibiting a trend towards greater concentration.

4.1.2 Cluster Analysis

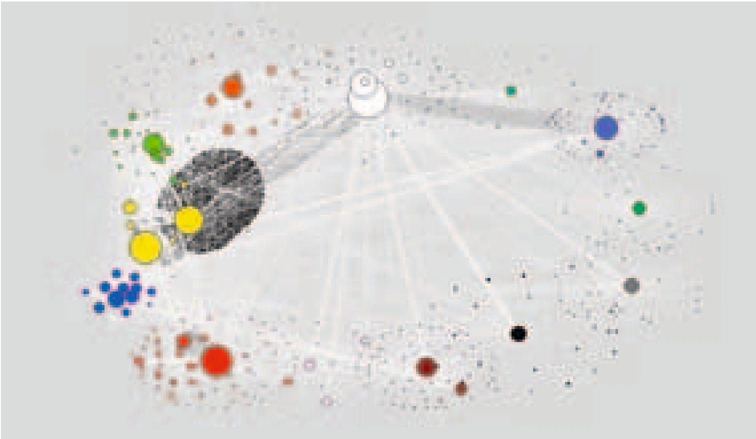
As quantified by Boss et al. (2004) the Austrian banking system is heavily tiered and clustered. The *Raiffeisen* sector comes with a three-tier structure (with intermediate institutions in Austria's federal states), whereas *Sparkassen* and *Volksbanken* are organized in a two-tiered system. Applying Pajek's[33] version of the Louvain algorithm[34] we identify 13 communities consistent with "expected" sectoral boundaries. Charts 5 and 6 show the evolution of these 13 clusters from end-2008 to end-2011 respectively.[35]

The clustered loan networks (see charts above) confirm what we have observed in the previous section. The decrease of inter-cluster connectivity has contributed substantially to the loss in overall *density* of the network from 1.6% (end-2008) to 1.2% (end-2011), after a peak of 2.3% in Q3 2010.[36]

Putting all observations from section 4.1 together, we find that (i) the interbank lending network's *density* decreases over time (particularly since Q3 2010), while (ii) the central *nodes* become more important (as measured by *Katz centrality* variance). Moreover, we are able to characterize (iii) a fairly stable network structure that reflects the historical development of the Austrian banking system.

Chart 5

Clustered Loan Network as at End-2008

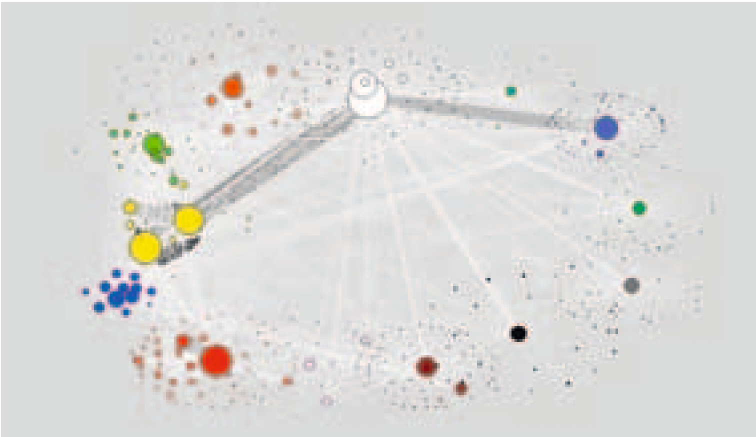


Source: OeNB calculations.

Note: Darker lines indicate a higher loan volume; the black bubble within the yellow cluster represents a very large in-cluster loan.

Chart 6

Clustered Loan Network as at End-2011



Source: OeNB calculations.

Note: Darker lines indicate a higher loan volume; the black bubble within the yellow cluster represents a very large in-cluster loan.

4.2 Stability: Contagious Defaults in Hypothetical Simulations

Whereas the (theoretical) literature about default cascades is even more abundant than the literature about financial systems as networks,[37] the published empirical evidence is limited. Hence we will not contribute to the former but try to add some to the latter. At the same time, the results of the hypothetical default simulations, while not the primary objective of our

[33] *See http://vlado.fmf.uni-lj.si/pub/networks/pajek for details.*

[34] *See Blondel et al. (2008). The algorithm optimizes modularity for a given resolution parameter, which is associated with a high proportion of links within a cluster – more than can be expected randomly.*

[35] *We are interested in "useful separation" rather than in discovering some "true" community structure.*

[36] *See also chart 1 (degree), as density is a linear transformation of the average degree.*

[37] *Before Eisenberg and Noe (2001) came Rochet and Tirole (1996), who focused on central bank policy options in a model of interbank lending, and Allen and Gale (2000), who studied how the banking system responds to contagion when banks are connected under different network structures.*

paper, are covered in the following section. We want to characterize some of the major observations related to *contagiousness* as well as *vulnerability* in our sample as those are important for the estimation of our panel models.

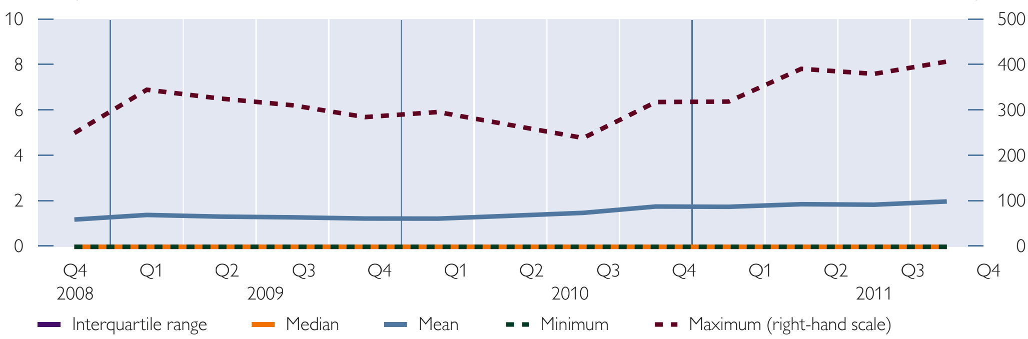
4.2.1 Default Indicators

As described in the methodology section (see 3.2) we explicitly target contagious defaults, i.e. those that are not caused by a fundamental weakness of a bank but those that follow the failure of another bank in the banking system. We simulate the default cascades of banks no longer honoring their commitments on the interbank market following Elsinger et al. (2006) and distinguish between *contagiousness* (the number of other banks that a bank brings down by contagion) and *vulnerability* (the number of banks by which a bank is brought down).

To describe their basic properties, we stick closely to the observations we made regarding the *degree* (see the beginning of subsection 4.1.1). On the one hand, the default indicators mirror

Chart 7

Contagiousness

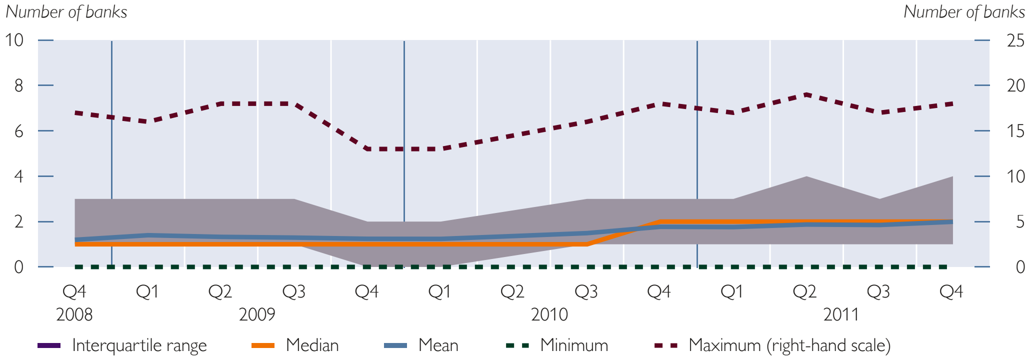


Source: OeNB calculations.

Note: The results are based on a sample of 749 Austrian banks from end-2008 to end-2011 (with the exception of Q2 2010 for which no data were available).

Chart 8

Vulnerability



Source: OeNB calculations.

Note: The results are based on a sample of 749 Austrian banks from end-2008 to end-2011 (with the exception of Q2 2010 for which no data were available).

the *degree* insofar as a few important/central *nodes* overshadow the many smaller banks. This is particularly true for *contagiousness* (see chart 7), where even the third quartile remains zero throughout the observation period. This pattern is less pronounced for *vulnerability* (see chart 8), which makes perfect sense insofar as by definition a bank with many creditors will not be as dependent on any single one of them, leading to a "natural boundary."

At the same time, a look at the development over time reveals that both default indicators increase from end-2008 to end-2011. This finding is particularly important, as it reveals an increase in *contagiousness* despite a reduction in the *density* of the Austrian interbank lending network. Defaults, to a certain degree, appear to have far more in common with the focal points of the network.

Given this observation, are central *nodes* central *nodes?* That is to say, is there a link between frequent defaulters irrespective of whether we look at the ones that cause high *contagiousness* or the ones affected by high *vulnerability.* Looking at the data we can see that while no bank's default is caused by more than 20 different institutions, some banks' fundamental default causes significant damage to the entire banking system. We note that despite the superficial similarity in the development of *defaults* and *weights,* there is no such similarity in depth. This observation will become important for our panel model in section 4.3, as it indicates that entirely different models are necessary to explain one or the other.

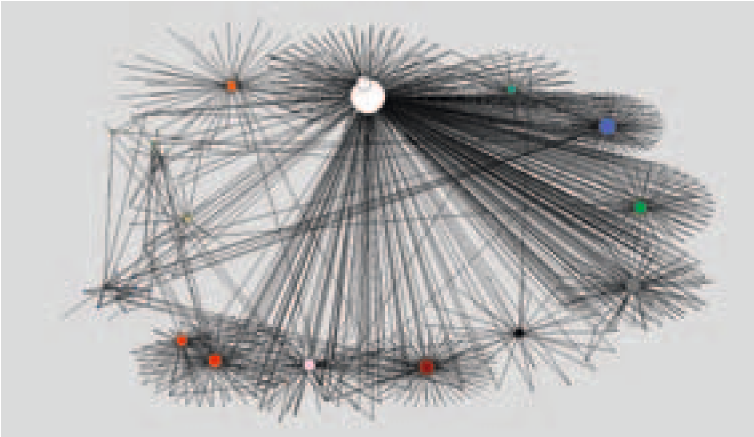
4.2.2 Default Networks

In analogy to section 4.1, where we interpret the interbank lending market as a network, we can do the same for the output of our hypothetical default simulations. Same as for the interbank liability matrix L, the default matrix D carries zeros in the diagonal, is of dimension $n \times n$, binary and not symmetric.

At end-2011 we compute an *average degree* of 3.2 and a *density* of 0.21%, while at end-2008 the corresponding network yielded 2.2 and 0.15% respectively. This is simply a restatement of the "increasing number of defaults" observation made above. In network terms one could say that the development is showing an inverse path compared to the loans-based network, resulting in a denser, more contagion-prone environment. However, with loan network *density* peaking in Q3 2010 when default network density was "only" at 0.19%, it appears that this trend has more to do with the more pronounced tiered structure than with mere overall *density.*

Chart 9

Contagiousness Network as at End-2011



Source: OeNB calculations.

Note: The results are based on the sample of 749 unconsolidated Austrian banks at end-2011 and end-2008, respectively. The node size represents the number of banks that the bank causes to default by contagion. The positions of the banks are the same as in charts 7 and 8.

4.3 Can Structure Explain Stability?

Having discussed the properties of our left-hand side variables, the next step is to find the properties of the banks/

banking system that can explain them. We first estimate a model for *contagiousness,* see section 4.3.1, then *vulnerability,* see section 4.3.2. As right-hand side variables we test for any combination of bank-specific indicators (from the OeNB's supervisory reporting system) and numerous network indicators that are calculated on (i) the network as a whole, (ii) a subnetwork or cluster, and (iii) the *node* level based on banks' interbank lending relationships.[38] We will only present one model for each default indicator. However, we will discuss how we arrived at those models, always keeping economic intuition as well as explanatory power firmly in sight.

4.3.1 Explaining Contagiousness

Understanding the determinants of *contagiousness* is one of the most challenging questions in modeling an interbank network. A systemically important bank could be defined as a bank that adversely affects a number of other banks in case it runs into trouble itself. In our regression we explained the impaired share of total banking assets since the mere number of caused defaults would obscure the actual cost (of a hypothetical bail-out) given the vast difference in size across our banks.

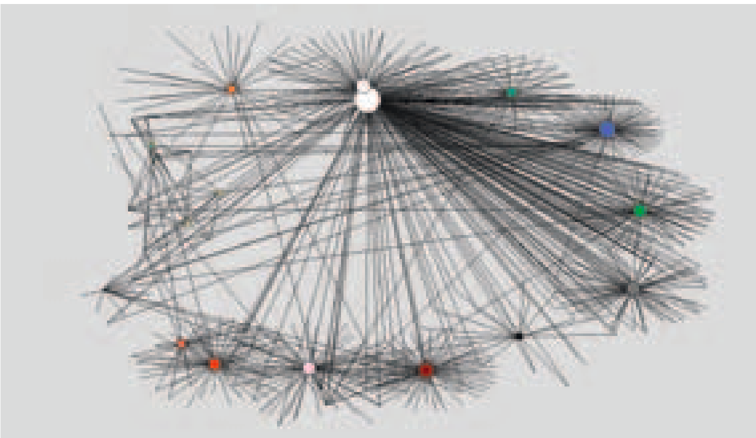
As a starting point, given the iterative nature of default dynamics, self-referential indicators appear as somewhat stronger candidates. *Eigenvector centrality* appears to be an obvious candidate and even yields acceptable regression statistics, but misses the point of the Austrian (tiered) loan network, since it is driven by cyclic areas in networks, and does not address the hub-and-spoke structure we observe as well.[39]

Betweenness centrality and *closeness centrality* have shortcomings as they are based on *shortest* paths, which carry no obvious interpretation in loan networks and indeed show little explanatory power for *contagiousness*. Our preferred network indicator is thus a modified version *of Katz centrality*. It takes into account that *nodes* without incoming *links* have no power to cause contagion (their *centrality* must be zero); banks with only incoming *links* have the power to cause contagion (their *centrality* must not be zero); the neighbors' neighbors matter as well as the loan sizes.

From the *centrality* layout chart (see chart 11), which shows banks with higher *Katz centrality* closer to the center, we can see that all banks with a high degree of contagiousness (illus-

Chart 10

Contagiousness Network as at End-2008



Source: OeNB calculations.

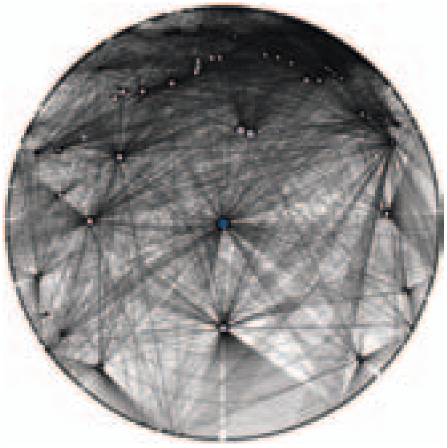
Note: The results are based on the sample of 749 unconsolidated Austrian banks at end-2011 and end-2008, respectively. The node size represents the number of banks that the bank causes to default by contagion. The positions of the banks are the same as in charts 7 and 8.

[38] *The latter were described in detail in section 3.1 and their respective realizations for the Austrian interbank lending network from end-2008 to end-2011 discussed in section 4.1.*

[39] *For a detailed discussion of Eigenvector centrality and related measures see Newman (2010), Bonacich and Lloyd (2001) and the forthcoming, extended version of this paper.*

Chart 11

(Katz) Centrality Layout



Source: OeNB calculations.

Note: Larger and darker circles represent higher contagion effects; the closer to the center the higher the Katz centrality.

Table 1

Panel Data Regression Statistics: Contagiousness

Fixed effects (within) regression

	b	se	t	p
WeightedKatz	1.63e-06	5.18e-07	3.15	0.002
_cons	.0010053	.0002355	4.27	0.000
sigma_u	.00833046			
sigma_e	.00350343			
rho	.84971309 (fraction of variance due to u_i)			
r2 within	0.296			
r2 between	0.712			
r2 overall	0.662			
N-observations	8976			
N-groups	749			

Source: OeNB calculations.

trated by darker color and larger area) are far away from the outskirts of the circle. On the other hand we find no small, light *nodes* near the center. So, banks which are granted many and/or large loans carry higher *Katz centrality* and tend to cause the most damage when defaulting.

In addition, we have tested for idiosyncratic characteristics of *nodes* by adding various asset- and capital-based indicators from the OeNB's supervisory reporting data. To our surprise, neither were those indicators adding to the explanatory power of our model, nor were they statistically significant.[40] This yields a simple model with *Katz centrality* as the only explanatory variable as our preferred model (see table 1), thereby demonstrating that network indicators do indeed add information to explain contagiousness unavailable in standard supervisory reporting data.

4.3.2 Explaining Vulnerability

Our second dependent variable, *vulnerability,* measures the vulnerability of a bank with respect to fundamental defaults at other banks. Thus, we explain how many times out of 748 simulations where one bank defaults at a time, the given (749th) bank defaults through contagion. To control for the difference between *fundamental* and *induced defaults* we add a *leverage ratio (capitalbyassets)* to the panel model.[41] However, it is not significant at the 10% level (see table 2). Again, the network properties seem to be more important in terms of explanatory power for *vulnerability* than traditional measures of risk-bearing capacity.

Since we hypothesize that *vulnerability* should be more dependent on network properties we select *outputdegree k-core (outputdegreekcore), cluster-density (clusterdensity),* the *number of banks in cluster (numbanksclu)* and the *clustering coefficient (clusteringcoeff~sone)* in our model.

In more detail, the rationale behind the selection is the following: The higher the order of *outputdegree k-core* of a bank, the more likely are alterna-

[40] *Again, we refer to the forthcoming extended version of the paper for a detailed discussion.*

[41] *The capital-to-assets ratio is based on the OeNB's supervisory reporting and defined as capital over assets.*

tive sources of funding and the less pronounced is the effect of a core member's default. This variable has by far the most predictive power even though no weighting was performed (i.e. cores are independent of loan sizes).

The coefficient of *cluster density* is also negative, which means that a higher degree of connectedness within one of the 13 previously identified clusters reduces *vulnerability*. Again, the bigger the number of banks in a cluster the lower their *vulnerability* since the portfolio diversification effect of interbank connections within a cluster reduces the likelihood of being contagiously affected by another bank.

Finally, the *clustering coefficient* measures the connectedness of one *node's* neighbors. As the *clustering coefficient* is on average one quarter of the average *cluster density* the *clustering coefficient* is an economically more important indicator for *vulnerability*.

The large number of variables (in comparison to the *contagiousness* model) can be attributed to the fact that our research suggests an even greater importance of the immediate vicinity of a *node* in explaining its *vulnerability*. Only the introduction of cluster variables yielded any statistically significant models with regard to explanatory power. This constitutes the most important finding of our paper, and adds value in particular with regard to Schmitz and Puhr (2009), where the authors faced similar difficulties accounting for *vulnerability* (albeit in the payment system world).

Table 2

Panel Regression Statistics: Vulnerability

Fixed effects (within) regression

	b	se	t	p
outdegreekcore	–0.018***	0.002	–8.113	0.000
clusterdensity	–0.294*	0.132	–2.229	0.026
capitalbyassets	–0.396	0.281	–1.410	0.159
numbanksclu	–0.001***	0.000	–4.265	0.000
clusteringcoeff~sone	–4.736***	0.937	–5.054	0.000
_cons	–0.825***	0.037	22.122	0.000
r2 within	0.114			
r2 between	0.411			
r2 overall	0.306			
N-observations	8976			
N-groups	749			

Source: OeNB calculations.

Note: p<0.05; ** p<0.01; *** p<0.001.*

5 Conclusion

By applying standard network techniques to our dataset of interbank lending relationships for the Austrian interbank market from end-2008 to end-2011, we were able to find ties between a bank's position in the lending network and its performance in hypothetical default simulations (conducted as part of OeNB's quarterly systemic risk assessment). To quantify these ties we used a panel model approach to link the defaults (dependent variables) to network and/or balance sheet indicators (independent variables).

With regard to a bank's *contagiousness* (measured in terms of the assets of any other banks that it would drag down if it were to default), the iterative nature of *Katz centrality* allows for a very good prediction of default cascades and also makes it possible to assess potential recapitalization requirements for the banking system, thus providing an alternative measure of systemic importance. The model does not take into account the distribution of a bank's neighbors' risk-bearing capacity or the proportion of loans to the bank's capital. These points together with further work to calibrate *Katz centrality*[42] provide possible paths for further development of the model.

[42] *In particular the search for an optimal attenuation factor* α.

For an assessment of the *vulnerability* of a bank (measured in terms of the number of defaulted banks that would cause a given bank to go down by contagion), we are able to show that adding more information about the structure of the banking system[43] by introducing cluster-network indicators improves the estimation of our panel model significantly. A possible route for refinement would be the introduction of a different configuration, possibly adding weights to account for loan size, of the *clustering* algorithm as well as looking at introducing a ratio for individual loans to capital. This should enable us to improve our measure of a given bank's *vulnerability* in terms of proneness to default by contagion.

Nevertheless, already at this stage we believe that our models provide a complementary look at a bank's risk profile for (macroprudential) supervisory purposes. Although we used a dataset constrained to unconsolidated banks from a single country, we are optimistic that our findings could be verified for other banking systems.[44] Finally, further refining our research (e.g. through a specific analysis of contagion channels), we can envisage recommendations for policymakers based on our work with regard to an adequate policy mix/communication strategy to possibly mitigate the risks associated with second-round effects, contagion risk and default cascades in the interbank market.

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[43] *The "known structure" in case of the Austrian banking system is its historically established banking sectors and their tiered structure.*

[44] *In particular it would be interesting to examine how the significance of network indicators is different in different banking networks and different capital level environments.*

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