Simulation methods to assess the danger of contagion in interbank markets☆

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ABSTRACT

Researchers increasingly turn to counterfactual simulations to estimate the danger of contagion owing to exposures in the interbank loan market. This paper summarises the findings of such simulations, provides a critical assessment of the modelling assumptions on which they are based, and discusses their use in financial stability analysis. On the whole, such simulations suggest that contagious defaults are unlikely but cannot be fully ruled out, at least in some countries. If contagion does take place, then it could lead to the breakdown of a substantial fraction of the banking system, thus imposing high costs to society. However, when interpreting these results, one has to bear in mind the potential bias caused by the very strong assumptions underlying the simulations. Robustness tests indicate that the models might be able to correctly predict whether or not contagion could be an issue and, possibly, also identify banks whose failure could give rise to contagion. They are, however, less suited for stress testing or for the analysis of policy options in crises, primarily due to their lack of behavioural foundations.

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1. Introduction

Will the failure of a financial institution trigger the subsequent failure of others? This is perhaps the most important question financial supervisors have to answer when faced with an institution in distress. For example, the US authorities' decision to bail out AIG in September 2008 was motivated by the fear that its "failure under the conditions prevailing would have posed unacceptable risks for the global financial system and for our economy" (Bernanke, 2009). Just over a year before, German authorities justified the takeover of IKB by state-owned KFW on similar grounds.

Knowing whether the failure of a particular institution could trigger the failure of others is important not only for crisis management but also for crisis prevention. Institutions whose failure would have large knock-on effects could be subject to more rigorous supervision or could face higher capital requirements in order to reduce the incentives to become "too connected to fail". Similarly, regulators could impose measures such as exposure limits to reduce the likelihood of contagion.

The interest in contagion has clearly gained momentum during the global financial crisis, but it is not new. The sell-offs in emerging markets after the Mexican peso crisis in late 1994 and the Asian crisis in 1997 triggered a large body of literature on contagion in financial markets.[1] A number of theoretical papers study contagion between financial institutions, but there has been relatively little empirical work in that area. In part this is because most institutions whose failure could give rise to contagion are rescued before they collapse. Most of the empirical literature in this area has therefore focused on lesser events and studied the response of asset prices (equity prices or risk spreads) of other banks,[2] although there are a small number of studies that looked at deposit flows after bank failures.[3]

The absence of solid empirical evidence on whether contagion is possible poses problems for central banks and other authorities in charge of safeguarding the stability of the financial system. Economists studying contagion have therefore resorted to simulation methods to test whether, given a particular set of exposures, failures could have knock-on effects. Initially, such simulations were primarily used on a stand-alone basis to estimate whether or

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[1] E.g. Bae et al. (2000), Forbes and Rigobon (2002) and Rigobon (2003).
[2] The seminal contribution is Aharony and Swary (1983). More recent papers are Hawkesby et al. (2007) and Gropp et al. (2009).
[3] See De Bandt et al. (2009) for an overview.

not a particular banking system was prone to contagion. A parallel strand of research embedded contagion modules into more comprehensive macroeconomic stress testing models. Recent examples are the Austrian National Bank's *Systemic Risk Monitor* (Boss et al., 2006) and the Bank of England's *RAMSI* (Alessandri et al., 2009).

In the present paper, I review the methodologies behind simulation methods to test for contagion in interbank markets. I then discuss the results of the various exercises in light of the explicit and implicit modelling choices, and conclude by suggesting possible ways forward. I restrict my attention to papers that study contagion driven by defaults on interbank lending. Contagion can also take place through many other channels (see Section 2), but by focusing on one particular channel of contagion it is possible to compare a relatively homogenous set of papers and discuss their underlying assumptions in greater detail than would be the case with a broader focus. In this context, it is useful to distinguish between the *possibility* and the *severity* of contagion. The former refers to the whether or not contagion can take place if a given bank fails and the latter to the proportion of the banking system that is destroyed by contagion.

The paper is structured as follows. The next section discusses theoretical research that studies the interaction between network structure and the possibility for, and the severity of, contagion. Section 3 reviews the methodology used to perform the simulations. The following section discusses data issues. Section 5 presents the results of the exercises published so far. Section 6 assesses what we have learned, discusses the limitations of the methodology and suggests ways forward.

To give a brief summary of the findings, the literature reviewed here suggests that contagion due to interbank exposures is likely to be rare. However, if it does take place, it could destroy a sizable proportion of the banking system in terms of total assets. That said, it is not clear whether some of these more extreme results are the consequence of the very strong assumptions underlying the simulations. In particular, none of the simulations is based on a model that incorporates more than an extremely rudimentary behaviour by banks or policymakers.

2. Relationship to previous literature

2.1. Channels of contagion

Contagion can take place through a multitude of channels, which are summarised in Table 1.[4] The papers surveyed here focus on one particular channel, namely direct effects due to losses on interbank loan exposures (marked in italics), although some also consider exposures from the payment system or securities and FX settlements. This raises two questions: first, does it make sense to analyse the individual channels separately rather than estimating their overall effect. Second, even if it does, should we focus on interbank exposures rather than any other channel.

The answer to the first question depends on the reason one is interested in contagion. If the focus is on whether or not contagion is possible, knowing the particular channel is clearly of second order relative to the overall impact of the failure. By contrast, distinguishing between the various channels is important if the intention is to prevent contagion, since this will affect which policy measures are likely to be effective. For example, position limits in the interbank market could prevent direct exposures from becoming so large that they could give rise to contagion, but they would do little to mitigate other effects.

Table 1
Possible channels of contagion in the banking system.

Channel	References
Liability side	
Bank runs	
Multiple equilibria/fear of other withdrawals	Diamond and Dybvig (1983), Temzelides (1997), Goldstein and Pauzner (2004)
Common pool of liquidity	Aghion et al. (2000), Acharya and Yorulmazer (2008b), Diamond and Rajan (2005), Brunnermeier and Pedersen (2009)
Information about asset quality	Chen (1999), Acharya and Yorulmazer (2008a)
Portfolio rebalancing	Kodres and Pritsker (2002)
Fear of direct effects	Dasgupta (2004), Iyer and Peydró-Alcalde (2005), Lagunoff and Shreft (2001), Freixas et al. (2000)
Strategic behaviour by potential lenders	Acharya et al. (2008)
Asset side	
Direct effects	
Interbank lending	Rochet and Tirole (1996), *studies reviewed in this paper*
Payment system	Humphrey (1986), Angelini et al. (1996), Bech and Garratt (2006)
Security settlement	Northcott (2002)
FX settlement	Blavarg and Nimander (2002)
Derivative exposures	Blavarg and Nimander (2002)
Equity cross-holdings	
Indirect effects	
Asset prices	Cifuentes et al. (2005), Fecht (2004)

If disentangling the various potential channels of contagion is important, on which one should we focus on? Previous experience does clearly not suggest that it should be direct contagion due to interbank exposures. I am not aware of any example of a bank that failed because of losses on its exposures in the interbank market, although the collapse of Herstatt in 1974 arguably came close (Davis, 1995).[5] The lack of historical precedent could mean two things: Firstly, this channel is simply not relevant and can thus be ignored. Secondly, the channel may well be relevant in principle but so far contagious defaults have been prevented by government bailouts. Since bailouts are undesirable because of moral-hazard considerations, ex ante measures to limit the possibility of contagion may increase welfare.

There are numerous recent and not so recent examples of authorities bailing out financial institutions in order to prevent contagion (of any sort, not just due to direct exposures). Almost three quarters of the 104 failures of (mainly large) banks considered by Goodhart and Schoenmaker (1995) involved a bailout of one form or another. More recently, in the 2007–2009 crisis, governments rescued almost all of the financial institutions of relevance that were about to fail. The important exception is, of course, Lehman Brothers, whose bankruptcy in September 2008 was followed by the worst financial crisis since the Great Depression.[6]

Another reason for being interested in the possibility of domino effects is that fear of direct contagion could trigger indirect contagion. There are several models in the literature in which the fear of losses on interbank loans (or similar exposures) trig-

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[4] See De Bandt and Hartmann (2001), De Bandt et al. (2009) and references in Table 1 for more information on the various channels of contagion.

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[5] Jorion and Zhang (2009) find evidence for direct contagion between non-financial firms, which tend to have larger individual exposures relative to capital than financial institutions.

[6] The precise mechanism for contagion remains to be explored. Gorton and Metrick (2009) argue that it was a bank run in the repo market.
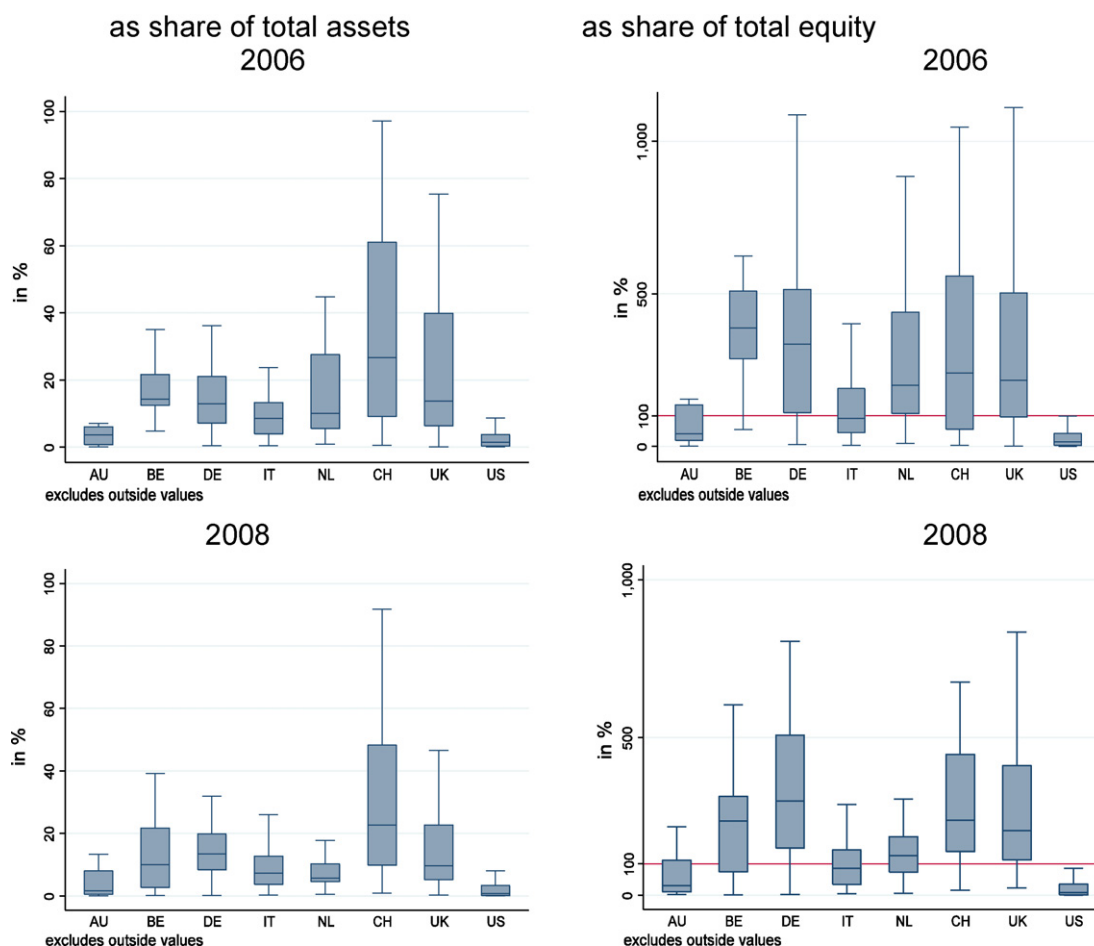
Fig. 1. Interbank lending. The box plots show medians, the first (Q1) and third quartile (Q3), and the lower and upper adjacent limits of the distribution of the particular ratios per country. To remove the effect of short-term volatility, total equity and assets for period T are calculated as the simple average of period $T-1$ and T. The lower and upper adjacent limits are calculated as $Q1 - [1.5(Q3 - Q1)]$ and $Q3 + [1.5(Q3 - Q1)]$, respectively. Outside values, i.e. the observations below the lower adjacent limits and above the upper adjacent limits, are excluded from the figures. In the case of interbank lending over average equity, observations below the 5% percentile and above the 95% percentile of the distribution of this ratio have been excluded.

gers bank runs (Dasgupta, 2004; Iyer and Peydró-Alcalde, 2005) or leads to gridlock as banks become unwilling to send payments or extent credit (Freixas et al., 2000). In an intriguing paper studying contagion after the failure of an Indian cooperative bank, Iyer and Peydró-Alcalde (2009) find that banks with larger exposures to the failing bank experienced larger runs by depositors.

Direct contagion can only happen if interbank exposures are large relative to the lender's capital. Fig. 1 shows that this is indeed often the case. Loans and advances to banks, a measure that excludes exposures through cross-holdings of securities and off-balance sheet instruments, not only account for a substantial proportion of many banks' total assets (left hand panels), but also are larger than many lenders' equity (right hand panels). According to the Bankscope database, at the end of 2006 the median bank's interbank assets exceeded its equity in 5 out of 8 developed countries. For many European banks, interbank assets exceed capital by a factor of five or more.[7]

2.2. Network structure and contagion: theory

A key insight of the seminal papers by Allen and Gale (2000) and Freixas et al. (2000) is that the possibility for contagion depends on the precise structure of the interbank market. Allen and Gale consider different lending structures in a banking system consisting of four banks that hold claims on each other. They show that for the same shocks some structures would result in contagion while others would not. In particular, a "complete" structure of claims, in which every bank has symmetric exposures to all other banks (panel a of Fig. 2), is much more stable than an "incomplete" structure (panel b), where banks are linked only to one neighbour. Disconnected structures (panel c) are more prone to contagion than "complete" structures, but they prevent contagion from spreading to all banks. Finally, Freixas et al. (2000) show that the possibility for contagion in a system with money-centre banks (panel d), where the institutions on the periphery are linked to banks at the centre but not to each other, crucially depends on the precise values of the model's parameters.

The theoretical models by Allen and Gale and Freixas et al. provide interesting insights, but it is not clear to what extent these can be extrapolated to the much more complex networks observed in the real world. Researchers have therefore turned to simulations to study contagion in more complex systems. The strand of the litera-

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[7] The figures for 2008 are roughly comparable. However, the position "loans and advances to banks" of Bankscope contains exposures to central banks, which are unlikely to lead to contagion. Such assets held at the central bank were relatively small in 2006 but large in 2008.
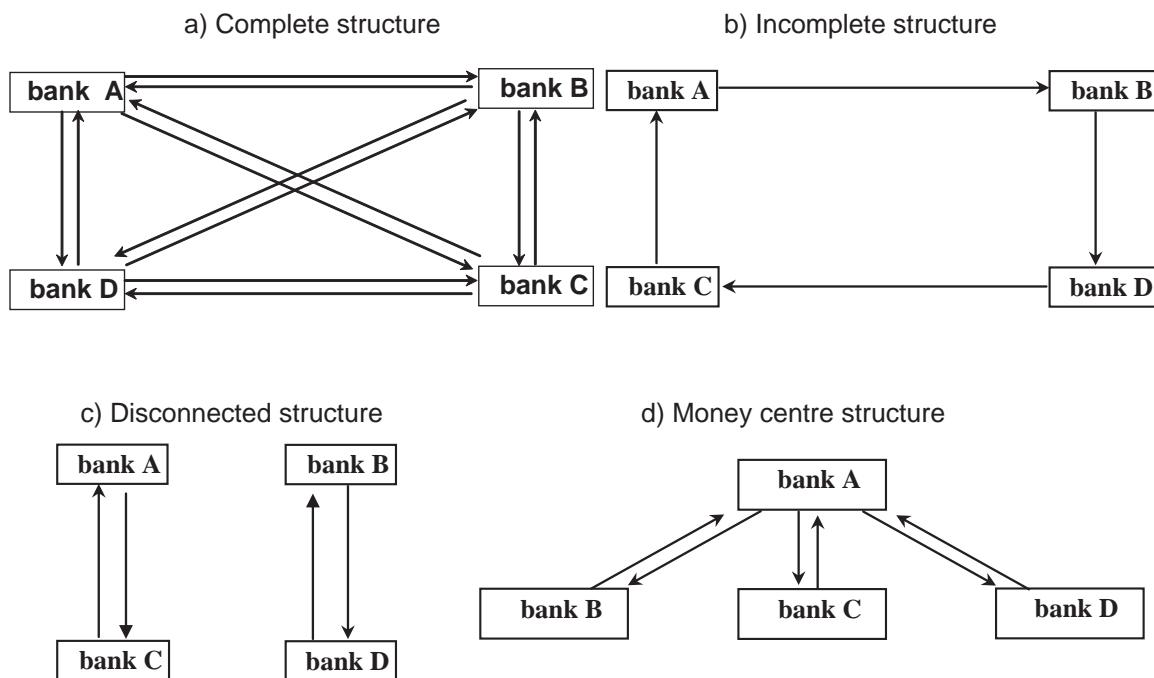
Fig. 2. Stylised network structures of the interbank market. (a) Complete structure; (b) incomplete structure; (c) disconnected structure; and (d) money centre structure.

ture reviewed in this paper uses data on actual exposures to test for the possibility of contagion. This shows whether a given banking system is prone to contagion, but it does not help us understand how particular features of the interbank market make it more prone to contagion.

Another strand of the literature, using the tools of network analysis, therefore analyses complex artificial networks with the aim of detecting patterns which could make them prone to contagion. For example, Nier et al. (2007) find negative and non-linear relationship between contagion and capital. The relationship between contagion and level of interbank lending to other assets is also non-linear. An increase in interbank lending from a low level has no effect on contagion, as losses are absorbed by capital. If interbank lending exceeds a threshold, then second round effects begin to appear and contagion increases quickly. Increasing the degree (which measures the number of connection between nodes) of the interbank network generates an M-shaped graph that reflects the interplay of two effects. On the one hand, adding more links increases the channels through which contagion may occur. On the other hand, any further increases raise the resiliency by sharing losses across a larger number of counterparts. The relative importance of the two effects depends on the level of connectivity and the amount of capital in the system.

3. Simulation methodology

An essential ingredient of any structural model for contagion is a notion of the links along which contagion may take place. In epidemiology, these links may represent physical contact, in international economics trade linkages. In our case, they represent credit exposures in the interbank market. The structure of such relationships can be represented either graphically,[8] or in matrix form.

Assets	Liabilities
a_i	l_i
NB_i	e_i

Fig. 3. Stylised bank balance sheet.

The latter approach turns out to be more useful for simulations of contagion.[9]

Fig. 3 shows a stylised bank balance sheet. For simplicity and without loss of generality, all nonbank lending NB_i is expressed as a net item on the asset side. Bank i's equity is written as e_i. Interbank lending appears on both the asset and the liability side of the balance sheet and is denoted by a_i and l_i, respectively. However, it is not aggregate exposures that matter for contagion but bilateral exposures. Let x_{ij} be the exposure of bank i vis-à-vis bank j such that $a_i = \sum_j x_{ij}$ and $l_j = \sum_i x_{ij}$.[10] The interbank market can be represented as an $N \times N$ matrix

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X = \begin{bmatrix} 0 & \dots & x_{1j} & \dots & x_{1N} \\ \vdots & & \vdots & & \vdots \\ x_{i1} & \dots & 0 & \dots & x_{iN} \\ \vdots & & \vdots & & \vdots \\ x_{N1} & \dots & x_{Nj} & \dots & 0 \end{bmatrix} \begin{matrix} \Sigma_i \\ a_1 \\ \vdots \\ a_i \\ \vdots \\ a_N \end{matrix}
$$

$$\Sigma_j \quad l_1 \quad \cdots \quad l_j \quad \cdots \quad l_N$$

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[8] See Boss et al. (2004), Iori et al. (2005), Iazzetta and Manna (2009), Lublóy (2005), and Müller (2006).

[9] The appendix of Degryse and Nguyen (2007) show how the stylised models of interbank markets considered in the theoretical literature can be shown as graphs and as matrices.

[10] I follow the convention of most papers to where the rows refer to assets and columns to liabilities. Some papers, mostly those using the Eisenberg and Noe (2001) clearing mechanism, specify a liability matrix L, where rows refer to liabilities and columns to assets.

where the zeros on the diagonal are due to the fact that banks do not lend to themselves.

With this notation in place, we can study the process of contagion. Suppose that bank i is hit by a shock $\varepsilon_i > e_i$ to nonbank lending that wipes out its equity.[11] As a consequence, bank i is no longer solvent and unable to repay its interbank liabilities l_i. To study contagion, researchers generally make the following assumptions:

Assumption 1. Banks have limited liability.

This assumption is at odd with the fact that virtually all banking systems feature institutions whose liabilities are either explicitly or implicitly guaranteed by the government or by other players. The only paper that studies the impact of explicit guarantees for contagion is Upper and Worms (2004). They find that the state guarantees for German saving banks and Landesbanks and cross-guarantees in the cooperative sectors substantially reduce both the possibility and the severity of contagion. Degryse and Nguyen (2007) do a similar exercise by assuming that the largest Belgian banks are not allowed to fail (too big to fail) and find that this reduces the severity of contagion in most but not all of their simulations.

Assumption 2. Nonbank liabilities are senior to interbank liabilities.

Whether this is an adequate depiction of reality is an open issue. Conversations with bank supervisors in Germany have shown that at least for that country some interbank claims are junior to deposits by non-banks, but others are not. The situation in other countries may be different, but it will probably be difficult to reach any general conclusions. In any case, it would be important for researchers to check the situation in the country they study. Most of the papers reviewed fail on this account. Falsely assuming that all interbank claims are junior to claims by non-banks will overstate both the possibility and the severity of contagion.

Assumption 3. Losses on interbank assets are shared equally across lenders.

Again, none of the studies reviewed here provides any detail on whether this assumption is grounded in reality. The biases can go into either direction.

Assumption 4. Nonbank assets NB_j can be sold at their book value.

It would be very surprising if banks failed without even trying to liquidate their assets, which would tend to depress prices and thus increase the severity of contagion.

Under these four assumptions, a creditor bank j will receive $\theta_i x_{ij}$, where $\theta_i = \max[(a_i + NB_i - \varepsilon_i/l_i), 1]$ are the losses-given-default associated with bank i's interbank liabilities. Contagion will take place if $\theta_i x_{ji} > e_j$ for some bank j. Computing the number of banks that will fail due to contagion is not trivial because any further failures reduce the value of assets, and thus losses-given-default, of the banks that have already defaulted. Eisenberg and Noe (2001) show that this problem has a unique solution – i.e. it is determined exactly how many and which banks fail due to contagion – and propose an efficient algorithm to deal with it.

3.1. Eisenberg and Noe's fictitious default algorithm

Eisenberg and Noe's algorithm to solve the problem of higher order costs of default works as follows:

1. Compute the losses to all banks resulting from the failure of bank i assuming that all other banks are able to repay their interbank liabilities. Stop if no further bank fails, otherwise.
2. Let j denote the bank or group of banks whose losses $\theta_i x_{ji}$ exceed their equity e_j. Compute the losses to all banks resulting from the failure of banks i and j. Repeat step 2 until no further bank fails.

The iterations in Eisenberg and Noe's fictitious default algorithm trace the path of contagion from the trigger to the first and higher rounds of contagion. However, it is important to keep in mind that the iterations are merely a computational device; in principle, contagion is instantaneous.

3.2. Sequential default algorithm

Eisenberg and Noe's fictitious default algorithm solves the problem of higher round feedback in the contagion process, but it has been used by only a small number of the papers reviewed here (see Appendix 1). Instead most papers use a sequential algorithm developed by Furfine (2003). It involves the following steps:

1. A bank i fails by assumption.
2. Any bank j fails if its exposure versus i, x_{ji}, multiplied by an exogenously given θ, exceeds its equity e_j.
3. A second round of contagion occurs if there is a bank k for which $\theta(x_{ki} + x_{kj}) > e_k$. Contagion stops if no additional banks go bankrupt. Otherwise a third round of contagion takes place.

In contrast to Eisenberg and Noe, this algorithm does not solve the simultaneity problem since it does not recognise that higher order defaults increase losses at the banks that have failed previously, which in turn raises the θ_i's on their liabilities. It is not clear whether the various authors using the sequential algorithm recognise this point. In any case, most papers using this algorithm assume that θ is constant across banks and rounds. Acknowledging the paucity of our current knowledge of loss-given default, they usually perform robustness checks by trying out a large range of values.[12]

3.3. Extensions: netting and bankruptcy costs

Several authors have extended the contagion algorithms described above to incorporate a number of features that are arguably of importance in real-world interbank markets. Upper and Worms (2004), Elsinger et al. (2006a) and Degryse and Nguyen (2007) performed robustness checks using net instead of gross exposures and found conflicting evidence on the extent to which netting reduces the possibility for contagion. In Upper and Worms (2004), netting led to a drop in the severity of the worst case of contagion from 76% of total assets to less than 10%. Similarly, in Degryse and Nguyen (2007), netting reduced the already low degree of con-

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[11] The assumption that only one banks is hit by a shock is for simplicity only. The analysis is virtually identical if several banks default.

[12] Historical evidence on losses-given-default in past banking crises gives little guidance in this regard. James (1991) found that the average loss realised in bank failures in the mid-1980s United States was 30% of the book value of the bank's assets. In addition, creditors had to bear administrative and legal costs of a further 10%. However, the banks in James' sample are overwhelmingly small and are probably of little relevance for the process of contagion. Kaufman (1994) argues that the losses to creditors of Continental Illinois would have been a mere 5% of the face value of their loans, had the bank not been bailed out. Bankhaus Herstatt's creditors had regained 72% of their claims by 1999, 25 years after the failure! At the time of failure, losses were expected to be much higher. In the case of BCCI, press reports at the time suggested that creditors expected to lose almost all of their exposures, but in the end recovered about one half.

tagion after the failure of a domestic bank even further. By contrast, Elsinger et al. (2006a) found that netting had only a small impact on contagion. Whether this is due to difference in the structure of the interbank market or due to the different types of scenarios used by Elsinger et al. is an open question.

Elsinger et al. also incorporated bankruptcy costs and found that these substantially, and in a non-linear fashion, increased the incidence of contagion. The results are almost identical for levels of bankruptcy costs of less than 10%, but contagion becomes much more frequent and more severe if they exceed that threshold. Since bankruptcy costs are equivalent to higher losses-given-default, this result is very much in line with the jumps in the incidence of contagion that other studies found for high θ's (see Section 5).

4. Data

No matter how sophisticated, simulations of contagion are only as good as the data they are based on. Unfortunately, information on bilateral exposures in the interbank market is scarce and often of limited quality. Interbank loans are usually arranged bilaterally, perhaps with the help of an interbank broker, and are settled over the larger value payment system. Individual exposures are therefore intrinsically unobservable for anybody except by the immediate counterparties. Electronic trading platforms that would have access to the records of the market as a whole exist only in a limited number of jurisdictions.

The opacity of interbank markets has led supervisors in several countries to require banks to report their bilateral exposures. In other countries, such information is available from credit registers, which collect data on all types of loans, not just interbank lending.[13] Alternatively, bilateral exposures can be estimated from balance sheet or payments data. This section discusses how these various data sources can be used to populate the interbank matrix X and examines potential biases arising from shortcomings in the data.

4.1. Credit registers and supervisory reports

The most reliable sources of information on bilateral exposures in the interbank market tend to be reports provided by banks to their supervisors or credit registers. In some countries, e.g. in Hungary (Lublóy, 2005), Italy (Mistrulli, 2007), and Mexico (Guerrero-Gómez and Lopez-Gallo, 2004), such reports are fairly complete and thus fully identify the elements of X. In the majority of countries, however, they are subject to some type of censoring. In some cases, they exclude off-balance sheet exposures (see e.g. Degryse and Nguyen (2007) for Belgium and Van Lelyveld and Liedorp (2006) for the Netherlands). In others they are subject to relatively large reporting thresholds (e.g. € 1.5 million in Germany) or cover only the largest exposures (see Van Lelyveld and Liedorp (2006) for the Netherlands, Toivanen (2009) for Finland, Blavarg and Nimander (2002) for Sweden and Müller (2006) for Switzerland).[14]

Incomplete reporting is likely to result in an underestimation of both the possibility and the severity of contagion, although the degree of the bias will vary. Reporting thresholds or the concentration on the largest exposures will tend to bias downwards

the results if small institutions fail but should make little difference otherwise. Potentially more serious is the absence of any information on off-balance sheet exposures, which will lead to an underestimation of the possibility for contagion for banks that have large derivatives positions on the asset-side of their balance sheets. Such banks tend to be relatively large and their failure should therefore have much more serious consequences than the breakdown of a small institution.

Unfortunately, there is hardly any work that has quantified the consequences of censoring. Van Lelyveld and Liedorp (2006) compare estimates obtained from the Dutch large exposure data (exceeding 3% of a bank's own funds) with those from a specially commissioned survey covering all domestic interbank exposures of the top 10 banks and obtain rather similar results. However, they are not able to compare how using any of the two censored datasets compares to what would be obtained from a full dataset covering all exposures.

4.2. Estimating bilateral exposures from balance sheet data

In the absence of direct information on bilateral lending, the elements of X can be estimated from banks' balance sheets. Banks generally report their total interbank assets and liabilities, in some cases even broken down by maturities, on a regular basis. To draw inferences on bilateral exposures, the researcher has to make assumptions on how banks spread their interbank lending across potential counterparties. This is necessary because combining the balance sheets of all banks results in an underidentified system. The matrix X has N^2 elements, but balance sheets give N asset positions and N liability positions, corresponding to the row sums a_i and column sums l_i of, respectively. In addition, we know that the elements on the diagonal of X are zero as banks do not lend to themselves. This leaves us with $N^2 - 3N$ degrees of freedom.

The standard in the literature has been to assume that

Assumption 5. Banks spread their lending as evenly as possible given the assets and liabilities reported in the balance sheets of all other banks.

In technical terms, this amounts to maximising the entropy of X. The concept of entropy originates from physics and was introduced into the contagion literature by Sheldon and Maurer (1998). Upper and Worms (2004) and Elsinger et al. (2006a) extended ME to handle zero entries on the diagonal of the matrix. The rationale for maximising the entropy of X can be illustrated by an analogy to Bayesian estimation, where researchers tend to use a uniform distribution if they are agnostic about a parameter. The aim of such diffuse priors is to provide no information that would influence the estimates. Translated to the current setting, this means that by maximising the entropy of X researchers do not impose any structure beyond the information contained in banks' balance sheets. This is the correct assumption if we do not have any prior information on market structure, but not otherwise. I will get back to incorporating such information into the priors below, after discussing how ME can be implemented and how it will affect the results.

Maximum entropy (ME) methods work as follows: With the appropriate standardisation, interbank assets a and liabilities l can be interpreted as realisations of two marginal distributions, $f(a)$ and $f(l)$, and bilateral exposures x_{ij} as realisations of their joint distribution, $f(a,l)$. If $f(a)$ and $f(l)$ are independent, then $x_{ij} = a_i l_j$. Unfortunately, the resulting matrix X has the unappealing feature that the elements on the main diagonal are non-zero if a bank is both lender and borrower, i.e. that banks lend to themselves. This problem does not necessarily disappear as the number of banks increases if interbank lending or borrowing is relatively concen-

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trated. We therefore need to modify the problem by setting $x_{ij} = 0$ for $i = j$ without dropping the assumption of maximum entropy. This can be done by minimising the relative entropy of a matrix $\mathbf{X}^*$ with elements $x_{ij} = a_i l_j$ for $i \neq j$ and zero for $i = j$ with respect to the previous maximum entropy matrix $\mathbf{X}$.

$$\min_{\mathbf{x}_*} \mathbf{x}^{*\prime} \ln \frac{\mathbf{x}^*}{\mathbf{x}}$$

s.t. $\mathbf{x} \geq 0$ and $\mathbf{A}\mathbf{x}^* = [a', l]'$, where $\mathbf{x}^*$ and $\mathbf{x}$ are $(N^2 - N) \times 1$ vectors containing the off-diagonal elements of $\mathbf{X}^*$ and $\mathbf{X}$, respectively, a and l are the marginals, and A is a matrix containing the adding-up restrictions $a_i = \sum_j x_{ij}$ and $l_j = \sum_i x_{ij}$. Since the objective function is strictly concave, the problem has a unique solution that can be calculated using the RAS algorithm that is commonly used to compute input–output tables.[15]

The identifying assumptions underlying ME have strong implications. In particular,

1. All banks hold virtually the same portfolio of interbank assets and liabilities, differing only by size and by the fact that no bank has any claims on itself.[16]
2. All $x_{ij} > 0$ if $a_i, l_j > 0$. This means that ME has difficulties in reproducing incomplete or disconnected structures of the interbank market.

Taken together, these two properties mean that ME will not be able to reproduce a number of stylised facts on interbank markets such as the sparseness of $\mathbf{X}$ or tiering.[17] For example, Cocco et al. (2005) and Guerrero-Gómez and Lopez-Gallo (2004) show that banks transact only with a limited subset of all other banks. This could be explained by fixed costs for screening of potential borrowers and monitoring loans which may render small exposures unviable or for some other reason that remains to be explored. Similarly, Upper and Worms (2004) and Craig and von Peter (2009) provide evidence for tiering, where lower tier banks do not lend to each other but transact only with top tier banks, which tend to be tightly linked.

The inability to reproduce some properties of real world interbank markets means that any estimates obtained from ME will be biased. While I am not aware of any general theoretical results, intuition suggests that the risk sharing that comes from diversified bank portfolios would tend to lead to an underestimation of the possibility for contagion and an overestimation of the severity of contagion. This intuition is borne out by simulations. Mistrulli (2007) finds that for Italian data dating from end-2003 ME leads to an underestimation of contagion for low θ and to an overestimation for high θ (Figure 7 in Mistrulli, 2007). Similarly, Degryse and Nguyen (2007) show that, for Belgian data from end-2002, contagion is more severe for large loss-given default in simulations using a matrix obtained by ME than in those based on information from the credit register, although this may also have to do with the relatively high cut-off point of 10% of own funds above which banks have to report their exposures. By contrast, Van Lelyveld and

Liedorp (2006) find that ME underestimates contagion relative to both the large exposures data and their specially commissioned survey.

Another drawback of ME is that it requires researchers to have access to the balance sheets of all potential counterparties. In practice, this has limited ME to domestic exposures, since the data collected by central banks tend to give a full picture only of domestic institutions. Commercial datasets, such as Bankscope, tend to cover large banks only and thus miss out potential counterparties, which makes them unsuitable for ME. As a consequence, another assumption stemming from the use of ME is

Assumption 6. Contagion is only driven by domestic exposures.[18]

Assuming away contagion from abroad will lead to an underestimation of both the possibility and the severity of contagion.

Given the obvious drawbacks of ME, why have researchers turned to this approach? When Sheldon and Maurer (1998) introduced the concept into the literature there was very little information on the structure of the interbank lending network that could have been used as a basis for alternative identifying assumptions. In that case, using ME to obtain unconstrained estimates was the right approach. Of course, this argument no longer applies, since we do have prior knowledge about the structure of $\mathbf{X}$. In this case, ME should be adjusted to reflect this knowledge, something which is discussed in the next section.

4.3. Combining balance sheet data with other sources of information

Some of the shortcomings of ME can be mitigated by combining the method with other sources of information. In this subsection, I will discuss three types of additional information that could easily be incorporated: (i) particular elements of $\mathbf{X}$ are known exactly (including zero restrictions), (ii) the maximum size of particular elements of $\mathbf{X}$ are known, for example because of regulatory constraints, (iii) the researcher has an overall idea of the structure of the market, such as the presence of tiering, but cannot express this in terms of simple equality constraints.

Incorporating known elements of $\mathbf{X}$ is trivial. In this case, the known x_{ij}'s are dropped from the estimation routine and their values are deducted from a_i and l_j before using the RAS procedure to estimate the unknown elements of $\mathbf{X}$ only. Toivanen (2009) combines survey data for the top 6 Finnish banks with ME for the remaining banks in this way. The second case is more difficult and requires the use of an extension of the RAS algorithm by Blien and Graef (1991) that is able to accommodate such inequality constraints. The reader is referred to that paper for details.

The third case, where we have some idea on the distribution of exposures that cannot be expressed in simple equality or inequality constraints, can arise if balance sheets and credit registers cover different types of exposures. For example, the British large exposures data analysed by Wells (2002, 2004) captures uncollateralized positions only and includes off-balance sheet exposures such as derivatives or contingent liabilities. By contrast, banks' balance sheets report book loans only, without distinguishing between collateralized and uncollateralized exposures. Wells deals with this problem by assuming that banks' book loans are distributed across counterparties identically as the large exposure data, which he uses as to construct the matrix $\mathbf{X}$ of the ME problem set out above.

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[15] See Miller and Blair (1985) and Blien and Graef (1991) for details on the algorithm.

[16] These limitations become less of a problem if $\mathbf{X}$ is made up of several submatrices corresponding to different maturity buckets or types of exposures. For example, German banks are required to break down their interbank assets and liabilities into several maturity bands and single out exposures to counterparties belonging to the same "pillar" of the banking system. This enabled Upper and Worms (2004) to estimate a total of 25 matrices, which they add up to a single, systemwide matrix that is used in their simulations.

[17] A matrix is sparse if most elements are zero. Tiering takes place if subsets of institutions differ in the number and nature of links they have.

[18] In some cases, researchers are able to test whether shocks abroad could serve as a trigger for contagion. Second and higher order effects, however, are purely domestic.

4.4. Estimating **X** from payment data

Bilateral exposures can also be estimated from payment data. This approach has been pioneered by Furfine (2003) for the federal funds market. The idea is quite simple: any loan with a maturity of, say, one day, involves both a transfer of funds from the lender to the borrower on day zero and a payment of opposite sign on day one. Since loans are usually denominated in round amounts and interest is capitalised at repayment, one simply has to search all transactions of a large-scale payment system for possible repayments and then identify whether there has been a payment of the same amount minus interest but the opposite sign on the previous day.

Using payments data to construct **X** has a number of advantages and drawbacks. Such data has the advantage that it is able to see through window-dressing, since a matrix **X** can be estimated for each trading day, not only the last business day of a month or a quarter, as is often the case with methods based on surveys or balance sheets. On the downside, exposures can only be identified after having being repaid. This means that **X** is obsolete by construction. Furthermore, although in principle exposures of all maturities can be reconstructed from payments data, in practice it is applicable only to loans of a set of relatively short maturities. This is illustrated that all papers using such methods that I am aware of confine themselves to overnight loans.

The Furfine method makes a number of implicit assumptions:

Assumption 7. All payments are routed through the particular payment system(s) the researcher has data for.

Assumption 8. Interest is added to principal at repayment.

Assumption 9. Interest is in a particular range specified by the researcher.

Violations of any of these assumptions will result in an underestimation of both the possibility and the severity of contagion.

The reliability of such estimates depends on whether interbank loans are standardised in a way that allows them to be filtered out of payment data, and on whether payments are routed through the same system. In Denmark, all conditions appear to be fulfilled, and Amundsen and Arnt (2005) are able to fully match the exposures reported by banks on a number of control days. In other countries, however, the method may be less reliable. For instance, Demiralp et al. (2004) find that some US banks split interest rate payments from the repayment of the principal, which introduces a substantial downward bias into Furfine's data.

5. Results

According to my count, over 15 studies simulating contagion in the interbank market had been published by the time this paper was last revised in late 2009 (see list in Appendix 1). The setup presented in the previous section can deal with any number of bank failures that could trigger contagion, but despite this flexibility the majority of papers focus on the unanticipated failure of individual banks. While such cases are not unheard of,[19] the available evidence (including the latest crisis) indicates that the vast majority of banking crises followed shocks that hit several banks simultaneously rather than domino effects from idiosyncratic failures.[20]

Common shocks may weaken the resiliency of the remaining banks and thus increase the risk of contagion. Perhaps surprisingly, the number of papers analysing such common shocks is much lower than those considering single-bank failures. There is also a small set of papers focusing on contagion due to illiquidity.

5.1. Idiosyncratic shocks: exogenous failure of individual bank

A summary of the results concerning single bank failures is given in Fig. 4. The x-axis plots losses-given-default (all studies considering idiosyncratic shocks use the sequential default algorithm with exogenous θ to simulate default) and the y-axis shows the proportion of the banking system, measured by the share in total assets that is destroyed by contagious defaults (i.e. excluding the trigger bank).

Given the differences in the structure of the banking systems of the various countries and differences in the methodologies used, it is not surprising that few clear-cut results emerge. A first glance at Fig. 4 suggests that the danger of contagion is greatest in Germany and the Netherlands, where it may destroy institutions accounting for as much as three quarters of the banking system's total assets (Upper and Worms, 2004; Van Lelyveld and Liedorp, 2006) if losses-given-default are high. However, a closer look reveals that both scenarios actually have a probability of zero and that they are therefore devoid of any practical relevance. In the Dutch case, the "bank" triggering the catastrophic results actually represents the aggregated European banking system excluding Dutch banks, not any individual institution.[21] In Germany, the financial safety net in place at the time (end-1998) rendered the worst case scenario impossible. Allowing for guarantees from the state and from other banks limited contagion in the worst-case scenario to 15% of the German banking system. This is of a similar order of magnitude as the results obtained by Degryse and Nguyen (2007) for Belgium (20% of total assets), Mistrulli (2005) for Italy (16%), and Wells (2004) for the UK (16%). While below the apocalyptic scenarios discussed above, these numbers are substantial by any standard, especially if one considers that most surviving banks lose a substantial proportion of their capital.

By contrast, little possibility for contagion was found by Blavarg and Nimander (2002) for Sweden,[22] Lublóy (2005) for Hungary, and Sheldon and Maurer (1998) for Switzerland. Furfine (2003) and Amundsen and Arnt (2005) also report only a limited possibility for contagion, but their samples are limited to overnight transactions and hence do not provide a full picture of interbank lending.

The vast differences across studies could reflect differences not only in the financial systems of the various countries, but also in methodologies. To recapitulate the discussion in Sections 3 and 4, Table 2 summarises the various sources of bias stemming from the assumptions underlying the simulations. Unfortunately, few clear-cut results emerge. In part, this may be because the number of studies is rather small relative to the number of modelling choices. Moreover, many of the papers made rather similar assumptions, so there is relatively little variation. Nonetheless, is appears that the two studies using payments data (Amundsen and Arnt, 2005; Furfine, 2003) tend to find very little contagion. This could be because they limit themselves to overnight loans. By contrast, there is not obvious link between other estimation methods and the possibility or severity of contagion. For example, some of the stud-

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[19] Examples are the failures of Barings and BCCI, respectively. The former was brought down by losses piled up (and hidden) by a single trader in Singapore, while the latter had a very different business model and organisational structure than other banks.

[20] See Reinhart and Rogoff (2009) and Laeven and Valencia (2008) for recent studies of the origins of banking crises.

[21] By contrast, contagion due to the failure of a domestic institution affected at most 7% of total assets.

[22] None of the four major banks considered failed due to contagion after the failure of a major debtor, although there was one instance where a bank lost all its tier I capital following losses on FX settlement.

Table 2
Potential sources of bias.

Source of bias	Direction of bias		Amundsen and Arnt (2005)	Blavarg and Nimander (2002)	Degryse and Nguyen (2007)	Elsinger et al. (2006a)	Elsinger et al. (2006b)	Frisell et al. (2007)	Furfine (2003)	Guerrero-Gómez and Lopez-Gallo (2004)	Lublóy (2005)	Mistrulli (2007)	Müller (2006)	Sheldon and Maurer (1998)	Toivanen (2009)	Upper and Worms (2004)	Van Lelyveld and Liedorp (2006)	Wells (2004)
	Possibility	Severity																
Limited liability	−	−	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
Seniority of nonbank liabilities	+	+			√	√	√							√				
Equal sharing of losses	+/−	+/−	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
Nonbank assets can be sold at their book value	−	−			√	√	√							√				
Exogenous and constant θ	+/−	+/−	√	√				√	√	√	√	√		√	√	√	√	√
No bankruptcy costs	−	−			√		√							√				
No netting	+	+	√	√		√	√	√	√	√	√	√	√					
No derivatives exposures	−	−	√		√		√		√		√	√		√	(√)²	√	√	
Reporting thresholds	−	−		√	√	√		√						√			√	√¹
Maximum entropy	−	+				√	√							√	(√)²	√		
Only domestic exposures	−	−	√		√	√	√		√	√	√	√	√	√		√		√
Only overnight loans	−	−	√						√									
All payments routed through same system	0/−	0/1	√						√									
Interest is added to principal at repayment	0/−	0/1	√						√									
Interest is in a specific range	0/−	0/1	√						√									
Unanticipated failure of trigger bank	+/−	+/−	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
No policy interventions	+	+	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
No credit risk transfer	+/−	+/−	√		√	√	√	√	√	√	√	√	√	√	√	√	√	√
No safety net	+	+	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√

Notes: In case several methods are used, entries refer to baseline simulations. + overestimation, − underestimation, 0 no significant bias, +/− can go both ways, (√) applicable only to part of elements of **X**. (1) Large exposures data. (2) Only banks below top 6.
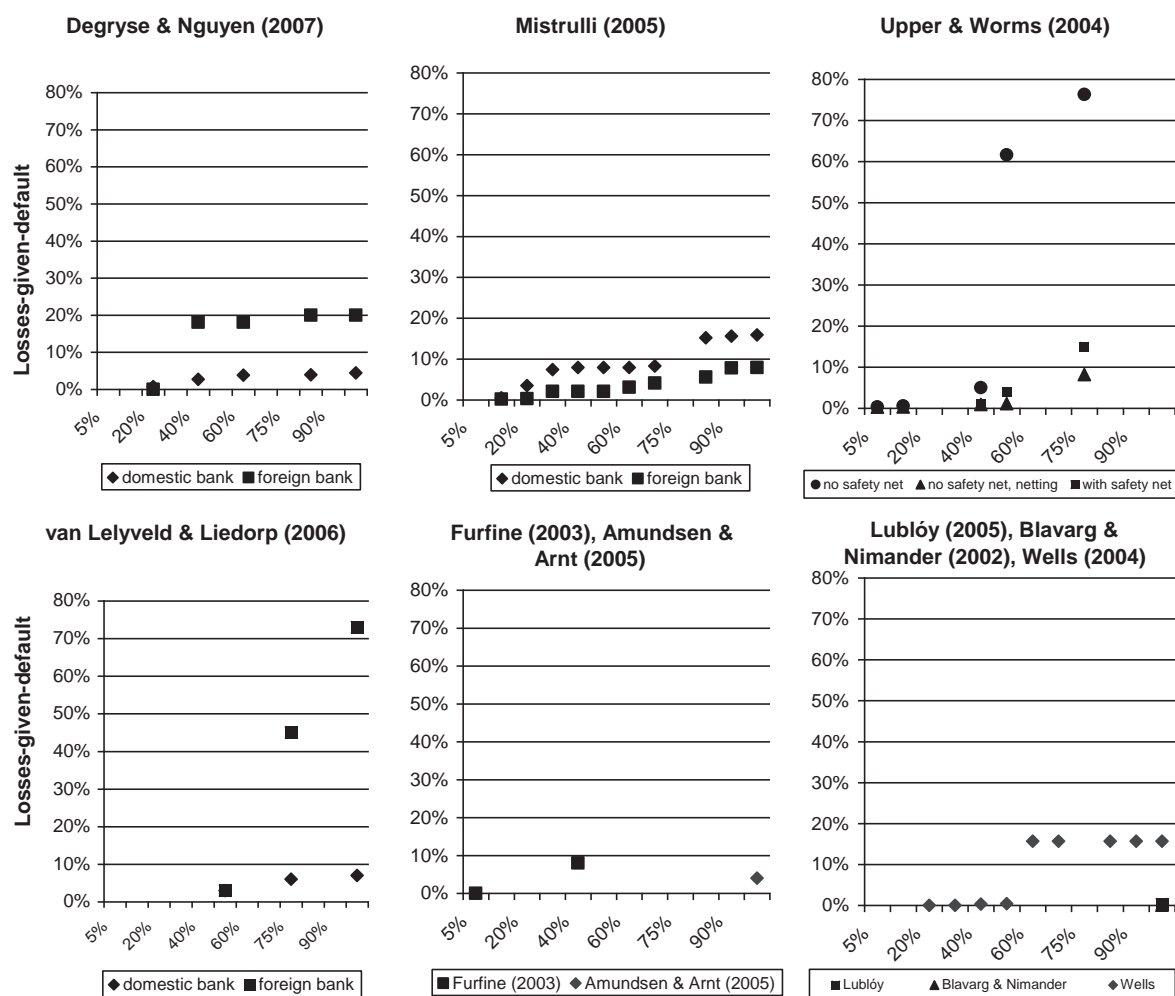
Fig. 4. Contagin due to idiosyncratic shocks. Vertical axis: % of total assets of the banking system destroyed. Horizontal axis: losses-given-default.

ies finding the severe contagion (Upper and Worms, 2004; Wells, 2004) use ME, which we found to be biased upwards. However, Degryse and Nguyen (2007) and Mistrulli (2005) also find severe contagion with survey data.

5.2. Systematic shocks: failures due to aggregate shocks

Failures due to common shocks could in principle be handled with the same tools as the ones used to analyse the effect of idiosyncratic shocks. Instead of letting individual banks fail, researchers have to specify groups of banks that are likely to fail together and follow the same procedure as for individual bank failures. However, this approach makes sense only if it is possible to define meaningful groupings of banks, for example based on their exposures to particular sectors. Perhaps for this reason, it has, to my knowledge, only been used once. Guided by results of stress tests undertaken on individual bank portfolios, Lublóy (2005) grouped banks according to their FX exposures let all banks in a given category fail jointly.

An alternative methodology in which multiple failures arise endogenously in response to aggregate shocks has been suggested by Elsinger et al. (2006a,b). In the first paper, they embed a matrix of interbank linkages of the Austrian banking system in a risk management model covering both market and credit risk. They then performed Monte Carlo simulations by drawing from the distri-

butions of the risk factors and computing the effect on each bank's capital. If banks became insolvent, they tested for the possibility for contagion to other institutions, which may already be weakened by the shock to their remaining assets.

Elsinger et al. (2006b) uses a different approach to model common shocks. Instead of relating the individual components on banks' nonbank portfolios to a set of risk factors, they use asset prices correlations to obtain a covariance matrix for the shock process, which substantially uses the data requirements to perform such a type of analysis. A similar approach has been applied to Sweden by Frisell et al. (2007).

The results of both papers by Elsinger et al., which rely on a variation of ME, indicate that contagious failures are rare compared to failures due to losses on exposures to non-banks. That said, if contagion does happen, it could affect a large part of the banking system. Moreover, contagion is much more likely in an environment where banks have already been weakened by common shocks. The second paper shows that ignoring the correlation structure of the processes driving banks' distances to default and interbank linkages results in a considerable underestimation of the probability of a systemic crisis.

Contagion is much more common in the simulations of Frisell et al. (2007). At θ=0.4, contagion occurs in approximately one half of all cases in which one of the top 4 Swedish banks fails. This could either reflect the more concentrated nature of the Swedish banking

system, or it could be due to the use of ME by Elsinger et al., which tends to reduce the possibility for contagion.

5.3. Liquidity

The studies reviewed so far were only concerned with cases in which contagion arose as consequence of the insolvency of the trigger bank(s). Liquidity entered the models only through the back door, via its effect on losses-given-default. Furfine (2003) and Müller (2006) have looked at the role of liquidity in the contagion process, although their scenarios differ considerably.

Furfine (2003) considers the case where the largest lender in the federal funds market for some reason that is exogenous to the model is unable to lend, thus forcing its counterparties of that institution to look elsewhere for funds and/or reduce their own lending. Under the assumption that banks can only borrow from and lend to institutions with which they previously had a similar transaction,[23] the withdrawal of the largest lender from the market could result in sizable liquidity shortfalls (defined as exceeding 10% of their actual federal funds borrowing on that day) for as many as 50 institutions. However, this result is almost certainly biased upwards, as Furfine is not able to take into account other source of liquidity, e.g. cash holdings or securities that could be used as collateral in the repo market.

Illiquidity may not only amplify contagion, but also cause it. An interesting simulation by Müller (2006) considers the effect on solvency and liquidity of a complete unwinding of all interbank lending. Initially all banks were solvent, but about 20% of the banks, representing just over half of total assets, did not have enough liquid assets to fully repay their obligations immediately and had to default. These defaults then led to the illiquidity and insolvency of some of the creditor banks. Overall, her simulations indicate that the immediate unwinding of the interbank market would lead to the illiquidity of almost 90% of the Swiss banking system, measured in terms of total assets, and the insolvency of just under 5%.

In an extension of her base scenario, Müller analysed how the ability to draw on credit lines affects the possibility for contagion. In principle, the possibility of drawing on a credit line could have two opposing effects. For the borrowing bank, credit lines provide a source of liquidity and thus reduce the likelihood of default. For the creditor bank, by contrast, this would result in a liquidity shock, which itself could lead to default. In Müller's simulations, the first effect dominated and the existence of credit lines reduced the possibility for contagion.

6. Discussion and possible ways forward

The models reviewed in this paper have been developed before the problems in the US subprime mortgage market grew into the most severe financial crisis in living memory. They clearly did not predict the crisis and, to my best knowledge, did not play any significant role in shaping any policy decisions during this period. Does this mean that they have been useless (and will remain so in the future)? In this section, I will argue that the usefulness of the models has been limited by two major shortcomings: (i) an exaggerated focus on scenarios involving the idiosyncratic failure of an individual bank rather than common shocks, and (ii) the absence of behavioural foundations that precludes the analysis of different channels of contagion.

6.1. Better scenarios

There are two possible reasons for the relative neglect of common shocks. One view would see this as a natural progression of knowledge: start with simulating scenarios that are easy to implement to understand the models we are using before turning to more realistic scenarios that are more difficult to simulate. A less benign view would argue that the focus on idiosyncratic failures reveals a worrisome lack of thinking about the scenarios underlying the simulations. While the truth may contain elements of both views, it is surprising that none of the papers looking at idiosyncratic shocks goes into much detail about why they chose this rather than another type of trigger event.

6.2. Behavioural foundations

Although better data and better scenarios would certainly help, a more fundamental problem is the absence of behavioural foundations. In the simulations surveyed here, banks sit tight as problems at their counterparties mount, doing nothing to reduce their exposures or increase their capacity to bear losses. This may be the correct assumption if the initial default is completely unanticipated, but this is rare if it happens at all. In the vast majority of cases, problems at failing banks have been manifest for some time, giving their counterparties time to react by cutting credit lines, not rolling over maturing debt, or novating derivatives contracts.[24] At the very least, this implies that simulations are only useful if they are based on up-to-date data. But there is a second implication that is more difficult to address. Any one of these actions will increase the pressure on the problem bank and may thus precipitating its failure. The experience of Lehman Brothers is a case in point. CDS premia on Lehman's debt had been going up for several months before its default in September 2008 (Fig. 5). In consequence, Lehman found it increasingly difficult to place its debt, which ultimately led to its demise.

The models would not have been able to predict Lehman's failure, but this is not what they were designed to do in the first place. The key question is whether a state of the art simulation model would have been able to predict the shockwaves that Lehman's bankruptcy sent through the global financial system. The answer is probably no. No major institution failed because of losses on its direct exposures to Lehman, although uncertainty about these exposures and those to other institutions on the brink of bankruptcy led to a gridlock in the financial system. It is not that this mechanism for contagion was not known (see Table 1 for references), but the absence of bank behaviour in the models meant that it remained outside the scope of the simulations. That said, having the data on the exposures of the major investment banks worldwide and a simulation model in place might have helped reduce uncertainty.

Several recent advances in economic theory could help capture strategic behaviour by banks and authorities alike and thus enrichen the simulations. For example, Iyer and Peydró-Alcalde (2005) model the interaction between losses due to defaults in the interbank market and deposit withdrawals. The role of fire sales, which could add to the losses on interbank lending, is explored by Cifuentes et al. (2005). Including such channels in the simulations would represent a major advance and could considerably improve their applicability for a large range of policy questions.[25]

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[23] This assumption could be justified by the need to screen borrowers et ante.

[24] See Duffie (2010) for a discussion of what happens when a large investment bank defaults.

[25] The possibility of such fire sales also has ex ante effects on banks' liquidity holdings. This issue is explored in Acharya et al. (2009).

Fig. 5. Lehman Brothers – CDS premia.

7. Conclusions

The simulations discussed in this paper have advanced our understanding of contagion, in particularly after the unanticipated failure of individual banks. We have learned that such scenarios should not be taken too lightly, as studies have identified a number of banks whose failure could bring down of other banks and thereby affect a sizable proportion of the banking system. We have learned much less about the interaction of common shocks and contagion. More work in this area is clearly needed.

The simulations may be plagued by a series of shortcomings, but they provide as yet the only way of estimating the potential for contagious defaults in a real-world banking system that can distinguish between different channels of contagion. However, while the models have improved considerably since the first of such studies was undertaken more than ten years ago, there is still a long way to go until they become an integral part of the toolbox of any authority responsible for financial stability. In particular, more work is needed on how to incorporate bank behaviour.

How useful are the models surveyed in this paper for financial stability analysis? It appears that the glass is either half full or half empty, depending on the perspective. On the one hand, the simulations do seem to give a rough indication on whether or not domino effects could be an issue. If they remind policy makers that the fact that contagion was not observed in the past need not mean that contagion could not happen, then they have already made a big contribution. Moreover, they help to identify which banks are critical to the stability of the system. This is particularly important since the criticality of a bank is determined by its size or the structure of its balance sheet, which can be gauged not only from balance sheet data, but also from the interaction of its interbank assets and liabilities, its capital and its precise location in the interbank network. Unlike any other methodology, simulations are able to account for all of these factors simultaneously, thus offering new insights. For example, in their analysis of the Mexican banking system, Guerrero-Gómez and Lopez-Gallo (2004) found that the failure of some small banks could cause contagion (although not to big banks), an issue that arguably had been off the radar screen prior to their study. In practice, the use of simulations to identify

institutions whose failure could lead to contagion does not depend so much on whether they predict the extend of contagion with any reasonable degree of accuracy, but on whether the list of potential triggers is robust, i.e. that their identity does not vary if the simulation methodology is changed. While there is little published evidence in this regard, my own work on German data suggests that there are some banks that pop up regularly no matter how the model is specified.

The glass is half empty because the models are not ready to be used in stress testing exercises, in cost-benefit analysis or in assessing policy options during crises. First, the assumption that banks do not react after a shock has hit the system means that they can only be used to model events that are both unforeseen and take place within a very short period of time. This seriously limits their use in stress testing, which, almost by definition, is concerned with periods of rapidly changing market conditions in which banks tend to react very quickly. It is difficult to envisage any progress on this front unless models are built from first principles and incorporate strategic behaviour by the main actors. The second limitation of counterfactual simulations in policy analysis is provided by the absence of meaningful probability estimates, except in the Monte Carlo analysis of Elsinger et al. (2006a,b) and Frisell et al. (2007).

An interesting thought experiment is to imagine how useful more developed versions of the models would have been in predicting, preventing or managing the latest crisis. The answer is: probably not much. Direct on-balance sheet linkages have played only a minor role in the crisis. In part, this may have been to bailouts. The failure of Lehman Brothers – the only larger institution allowed to fail – led to large losses at many of Lehman's creditors, but no major institution failed, although this have been because of massive government support. However, losses on exposures to Lehman did trigger a bank run at large money market funds (see Kacperczyk and Schnabl, 2009), which do not feature in any of the simulation models.

It is not clear whether the simulation models could be adjusted in a way that would have made them useful in the crisis. First, the events since 2007 highlighted the importance of several mechanisms that would have to be included in such models. An incomplete list would include mark-to-market and mark-

to-model accounting (Borio et al., 2009; Laux and Leuz, 2009; Amel-Zadeh and Meeks, 2009), market illiquidity, Knightian uncertainty (Caballero and Simsek, 2009) and subtle institutional details such as the "breaking the buck"[26] phenomenon of money market funds. It is not clear how any of these features, let alone several of them, could be incorporated into a simulation model without sacrificing realism on other dimensions. Furthermore, it is probably impossible to predict ex ante which features will be relevant and which ones would only be a distraction. For example, while the phenomenon of "breaking the buck" that triggered the run could

certainly be modelled with the tools discussed here, in the absence of hindsight it is hardly conceivable that any researcher would have expanded the models in such directions.

To conclude, the models surveyed here are a useful tool in the toolbox of financial stability analysis because they highlight concentrations of risk, but they cannot form the core of a model that would help predict crises. I remain to be convinced that such a model is feasible. In the worst of all cases, it would give a false sense of security while still not being able to prevent crises.

Appendix A. Simulations of contagion

	Country	Data source/estimation method	Simulation method	Shock	Extensions
Amundsen and Arnt (2005)	Denmark	Domestic overnight loans, computed from payments data	Sequential	IE	
Blavarg and Nimander (2002)	Sweden	Supervisory reports on 15 largest exposures of top 4 banks, incl. derivatives and FX settlement floats	Sequential	IE	Impact on liquidity
Degryse and Nguyen (2007)	Belgium	Domestic interbank loans and deposits of Belgian banks, ME. Foreign exposures from supervisory report on interbank exposures exceeding 10% of capital	Sequential		(i) Endogenise θ (ii) Relate contagion to concentration and internationalisation of interbank market
Elsinger et al. (2006a)	Austria	Domestic interbank loans and deposits, ME, complemented with equality constraints	EN	MC	(i) Risk management model for credit and market risk of individual banks (ii) Bankruptcy costs (iii) Bilateral netting
Elsinger et al. (2006b)	United Kingdom	Domestic interbank loans and deposits, ME (data as in Wells, 2004)	EN	MC	Asset correlations from multivariate Merton model
Frisell et al. (2007)	Sweden	Supervisory report on largest 15 exposures of top 4 Swedish banks (excl. repo)	Sequential	IE, AE	Probability of failure (from Moody's KMV, linked by Gaussian copula), and hence probability of contagion
Furfine (2003)	United States	Overnight loans in federal funds market, computed from payment data	Sequential	IE	Illiquidity due to inability to fund
Guerrero-Gómez and Lopez-Gallo (2004)	Mexico	Supervisory report on interbank exposures (incl. securities, derivatives and credit lines in payment system)	Sequential	IE	Illiquidity due to inability to fund
Lublóy (2005)	Hungary	Supervisory reports of all domestic interbank loans	Sequential	IE, AE	Topology of interbank market
Mistrulli (2007)	Italy	Supervisory reports of all domestic interbank loans	Sequential	IE	(i) Effect of intra-group guarantees (ii) Examines biases from loans
Müller (2006)	Switzerland	Supervisory reports covering 10 (20 for the two big banks) largest interbank exposures and liabilities (incl. off-balance sheet) of Swiss banks	EN	IE	(i) Topology of interbank market (ii) Illiquidity due to inability to fund
Sheldon and Maurer (1998)	Switzerland	Domestic interbank loans, ME aggregated by bank type	Sequential	AE	Probability of failure of trigger bank and hence probability of contagion
Toivanen (2009)	Finland	Supervisory reports on top ten interbank exposures of 6 largest banks, excl. repo; ME for remaining exposures	Sequential	IE	
Upper and Worms (2004)	Germany	Domestic interbank loans, ME performed separately for different maturity categories and bank types	Sequential	IE	(i) Bilateral netting (ii) Impact of safety net
Van Lelyveld and Liedorp (2006)	Netherlands	(i) Domestic interbank loans, ME (ii) Supervisory report on interbank exposures (incl. off balance sheet) larger than 3% of capital (iii) Survey of top 10 banks' for all domestic and top 15 foreign interbank exposures	Sequential	IE, AE	
Wells (2004)	United Kingdom	(i) Domestic interbank loans, ME (ii) Supervisory report on domestic and foreign exposures exceeding 10% of Tier 1 capital for some banks, ME for remaining banks	Sequential	IE, AE	(i) Estimate money-centred structure using ME and supervisory reports assuming that small banks hold all deposits with large banks

Notes: ME, maximum entropy estimation with balance sheet data; IE, idiosyncratic, exogenous (exogenous failure of individual banks); AE, aggregate, exogenous (exogenous failure of group of banks); MC, Monte Carlo analysis leading to endogenous failures.

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[26] This occurs if the asset value of a money market fund falls below the face value of its certificates.

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