Bank networks, interbank liquidity runs and the identification of banks that are Too InterConnected to Fail

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Abstract

We simulate interbank market contagion, enriching the standard transmission channel based on credit losses and capital, with new channels like funding liquidity losses, fire assets sales and active liquidity runs on infected banks, employing a testing dataset of Russian bilateral interbank exposures. Allowing active liquidity runs on infected banks is crucial to capture reality with the simulations. We use the simulations to calculate a bank's potential contribution to contagion, which serves as our measure of systemic importance. We find that the K-shell index, a new measure of interconnectedness, is the only robust and reliable predictor of a individual bank's potential to spread contagion, rather than size. Coreness should therefore not be confounded with size.

JEL: C8, G21

Keywords: interbank market, contagion, banking crises, systemic risk, network topology, tiering, Too-Interconnected-to-fail, K-core centrality

1 Introduction

There is an apparent puzzle at the heart of the 2007-2012 financial crisis. The 2007 estimates of the likely total losses on subprime mortgages were roughly equivalent to a single day's movement in the U.S. stock market (Adrian and Shin, 2008).[1] The resulting conventional wisdom in policy circles up to the summer of 2007 was that the subprime exposure was too small to lead to widespread problems in the financial system. Yet, reality proved different. The credit crisis developed with a ferocity that led some observers to characterize it as one of the worst financial shocks that the United States has confronted since the Great Depression (Mishkin, 2008). The presumption that subprime exposures did not pose a serious threat to the financial system could be justified by the

[1] Upwards revised estimates reported in Greenlaw et. al. (2008) still remain small in relative terms.

"domino" model of financial contagion. This model works through direct credit losses depleting bank capital. This simplistic "domino" model of contagion turned out to be a poor description of reality. The crucial variables in this model are credit losses and capital, measuring the simulated harm done by a bank's default and the residual banks' ability to either absorb the concurrent losses or succumb and propagate the shock over the banking network. Simulation studies performed by several central banks relying on this approach uncovered limited risk of a systemic meltdown (see Sheldon and Maurer (1998) for Switzerland, Furfine (2003) for the U.S., Upper and Worms (2004) for Germany, Lelyveld and Liedorp (2006) for the Netherlands, and Degryse and Nguyen (2007) for Belgium). These estimates of limited systemic risk contrast sharply with the broad financial disruptions experienced in 2007-2009 (the financial crisis ensuing after the meltdown of securitized lending and the ultimate collapse of Lehman Brothers), and 2010-2012 (the eurocrisis). The seeming empirical irrelevance of the early simulations of contagion on the interbank market is explained by a few crucial factors: Most, though not all, of these papers lack detailed bilateral and time-varying data on interbank exposures. The early literature relied on credit losses depleting capital and therefore spreading over a fixed banking network, largely neglecting a plethora of other possible channels like information contagion, funding liquidity problems, fire sales and asset losses, and the time-varying topology of the network itself. Most of these early simulation exercises are based on sample periods devoid of interbank market instability and characterized by a stable network structure. By consequence these studies exclude the possibility that the structure of the network itself may be subject to an abrupt phase transition in the run-up to the crisis, moving from liquid state to illiquid state in a highly non-linear way. In this paper we try to address some of these problems and propose a new way of simulating and interpreting interbank market contagion. We use this approach to identify those banks that are super-spreaders of contagion or, in the jargon of the banking literature, those that are to interconnected to fail. We proceed by showing that these superspreaders can reliably be identified by one simple network measure borrowed from physics, that measures the tieredness of the network and the tier in which a bank is situated. This is in line with the findings of Krause and Giansante (forthcoming). They study how the exogenous failure of a single bank spreads through the banking system and causes other banks to fail in a theoretically generated model and find that the determinants of whether contagion occurs include aspects of the network structure, namely the interconnectedness of nodes in the network and the tiering of the network.

In a first step we try to indentify which channels of contagion are sufficient to mimic real interbank market crisis. We start from various channels in the literature, namely the credit loss and capital channel, the liquidity loss channel, the asset value- fire sales channel, that take the topology of the network as given, and the funding liquidity losses channel, that includes behavioral aspects that endogenously affect the topology of the network during the crisis. We run simulations of these channels using the Russian interbank market as a training data set. The Russian data is very adequate for this exercise because the sample period covers two real, though very different, crises, and because the data quality is exceptional. We use bilateral and time varying contract data (maturities, prices, volumes) between all banks and monthly balances and profits and losses of the banks involved (between 500 and 800 depending on the period). We start from the simplest possible contagion channel, and simulate the damage to the banking system from killing a single bank. We repeat this for every bank and for every period and verify whether the results mimic reality, using the two real banking crises as a benchmark. Then we add increasingly more sophisticated channels making the contagion mechanism more realistic, till our simulated crises satisfactorily mimic both real life banking crises. That simulation is thus based on 1) real life time varying interbank contracts, 2) real life time varying bank level capital, liquidity, reserves and assets and 3) a sophisticated contagion scenario that mimics real crises. It turns out that we need the behavioral assumption of contagion through funding liquidity losses of infected banks to correctly simulate both real interbank market crises in our sample.

In a seond step we derive bank specific measures of a bank's contribution to contagion. Indeed, since we have identifies in the first step the approrpiate channels to simulate contagion, we can now calculate a bank-specific contribution to contagion, both during real interbank market panics and during calm periods (i.e. a counterfactual contribution if a crisis were to strike at that moment). The banks with a very high contribution to interbank market contagion have been labelled as systemically important institutions; It is important to identify them properly as higher loss absorbency requirements will be introduced for these banks in parallel with the Basel III capital conservation and countercyclical buffers, between 1 January 2016 and year end 2018 becoming fully effective on 1 January 2019. The assessment methodology for systemically important banks applies by the Basel Committee is based on an indicator-based approach and comprises five broad categories: size, interconnectedness, lack of readily available substitutes or financial institution infrastructure, global (cross-jurisdictional) activity and complexity. But it is still unclear how precisely to identify these banks and it has been suggested that size is the main indicator of systemic importance.

We provide a methodology to identify the banks that are too interconnected to fail in a third step. We show how we can predict this bank-specific contribution to contagion (and hence identify those that are systemically important) by just looking at the bank's position in the tiered network, disregarding all other bank-specific information and network measures. To this purpose we introduce the concept of K-coreness to the banking literature. It turns out that increasing network complexity (as expressed as the number of K-shells) precedes crises, and that the bank's K-shell index (a new measure of interconnectedness) strongly outperforms any other network indices in explaining a bank's contribution to contagion and also outperforms the size of the bank. By just looking at this one measure, we can explain between 30% and 40% of the bank-specific contributions to contagion. In short, we believe to have found a simple and robust measure to identify the banks that are systemicall important. Specifically, those that are systemically important turn out to be these that are Too-InterConnected-To-Fail, provided one has topological information of the network. We also show that even infomation about the 50% largest interbank market contracts (incomplete information) is sufficient to identify the systemically important banks.

In other work, we are also experimenting with characterizing the stability of the network itself by investigating whether any indications of a real phase-transition can be observed in the structure of the Russian inter-banking network. The theory of phase transitions and percolation theory are well developed in physics and found their way into network theory (Gai et al, 2011). In companion papers to this paper, we investigate how we can predict these phase transitions leading to liquidity freezes and the disintegration of the network. Most network analyses focus on "normal" periods of operation and stay away from systemic crises. The fact that two major crises hit the Russian banking system in the time period 1998-2004 that we wish to analyze, offers unparalleled opportunities.

2 Related literature

2.1 The simulation of contagion

Empirical studies of interbank market contagion include Sheldon and Maurer (1999), Blavarg and Nimander (2002), Upper and Worms (2004), Mistrulli (2007), Elsinger et al. (2006), Gropp et al. (2006), Lelyveld and Liedorp (2006), Müller (2006), Degryse and Nguyen (2007), Iori et al. (2008), Estrada and Morales (2008), Canedo and Jaramillo (2009), and Toivanen (2009). A general overview of the empirical methodology and the results obtained in many of the papers mentioned before can be found in Upper (2007). Upper (2011) gives a very complete overview of the various possible channels of contagion in the banking system proposed in the rich literature on this topic. Most of the early papers in the literature model how credit losses can potentially spread via the complex network of direct counterparty exposures following an initial default. In this paper we also simulate contagion by starting from credit losses on the interbank market, but we enrich this channel but also introducing aspects of liquidity, fire sales and network topology into the analysis. The standard approach is to study how credit losses in the interbank market directly affect the creditor banks' capital and liquidity and in this way generates further rounds of defaults and credit losses by propagation over a fixed and often not exactly known network. Our first contribution to this contagion literature is that we use data on exact bilateral time-varying exposures from a rich Russian dataset in combination with rich monthly information from bank balances and profit an loss accounts. Our data window of 75 months of bilateral contract data covers two isolated Russian interbank market crises, that give us two natural experiments to train our simulations.

2.2 Liquidity, fire sales and systemic risk

Our second contribution is that we move beyond the capital channel in several ways. Next to credit losses and bank capital, liquidity on the asset side of the balance sheet may play an important role. Cifuentes et al (2005) and Shin (2008) for example stress that financial distress at some financial institutions may have knock-on effects on asset prices and force other financial institutions to write down the value of their assets. Contagion due to the direct interlinkages of interbank claims and obligations may thus be reinforced by indirect contagion through the asset side of the balance sheet – particularly when the market for key financial system assets is illiquid. Next to asset liquidity, funding liquidity considerations may play a major role on the transmission of shocks on the interbank market. Rochet and Vives (2004) present a model where large well-informed investors refuse to renew their credit on the interbank market in the presence of a large adverse shock. An adverse shock to one bank may create uncertainty about other banks, possibly subject to the same shock. Since interbank market participants are generally risk averse and have asymmetric information about each other's financial health, banks may overreact to any negative news and withdraw their funds as quickly as possible. Such a generalized liquidity crunch may push a solvent institution into illiquidity and bankruptcy. This means that during a crisis the topology of the network not only changes because of defaulting banks, but also because banks reconsider their relations with otherwise healthy banks. This seems to be in line with the stylized facts of the 2008 interbank market panic, where contagion seems to have mainly run over liquidity linkages rather than solvency linkages, even if the underlying problem may be insufficient capital.

The Bank of England is developing the risk assessment model for systemic institutions (RAMSI) to sharpen its assessment of institution-specific and system-wide vulnerabilities. RAMSI considers interbank linkages and macro-banking linkages by analyzing three areas of interconnectedness: funding feedbacks, asset fire sales, and a real sector-financial sector feedback loop (Aikman et al, forthcoming). We incorporate the potential impact of funding liquidity contagion and asset fire sales in our simulations, but refrain from real macro feed-back loops.

Last it may be the case that simulations of idiosyncratic shocks miss the stylized fact, suggested by historical default data, that large fractions of the financial sector mail fail together (default clustering of financial institutions) due to both direct and indirect systemic linkages. Therefore it may be useful also to simulate the impact of correlated bank defaults on the stability of the interbank market, rather than just simulating the impact of idiosyncratic defaults. For the simulations presented in this paper we have used the method of random attack, but our results are very robust to initial correlated bank defaults. One may also want to look at the effects of contagion with and without the financial safety net as in Upper (2011). We did as much in our much earlier Bofit working paper (Karas et al., 2008), but in this paper we will focus on the transmission channels of asset fire sales and funding liquidity and on the network aspects of interbank market panics.

2.3 Networks

Our third contribution is that we also introduce the topology of the network itself into the analysis. Allen and Gale (2000).demonstrate that the spread of contagion depends crucially on the pattern of interconnectedness between banks, using a simple network structure with four banks. When the network is complete, with all banks having exposures to each other such that the amount of interbank deposits held by any bank is evenly spread over all other banks, the impact of a shock is readily attenuated. Every bank takes a small 'hit' and there is no contagion. By contrast, when the network is 'incomplete', with banks only having exposures to a few counterparties, the system is more fragile. The initial impact of a shock is concentrated among neighboring banks. Once these succumb, the premature liquidation of long-term assets and the associated loss of value bring previously unaffected banks into the front line of contagion. In a similar vein, Freixas et al (2000) show that tiered systems with money-center banks, where banks on the periphery are linked to the center but not to each other, may also be susceptible to contagion. The generality of insights based on simple networks with rigid structures to real-world contagion is clearly open to debate (Gai and Kapadia, 2011). Models with endogenous network formation (e.g. Leitner (2005) and Castiglionesi and Navarro (2007)) impose strong assumptions which lead to stark predictions on the implied network structure that do not reflect the complexities of real-world financial networks, while our dataset allows us to approach these real world complexities much closer. It is also important to dintinguish the probability of contagious default from its potential spread, as suggested in Gai and Kapadia (2011). We try do do as much in our simulations of contagion.

Our main interest is not the prediction of systemic risk, but the identification of the systemically important financial institutions (SIFI). In an interbank network context, these are the banks that are too interconnected to fail (TICTF). The empirical analysis of which banks contribute most to the interbank network contagion (who are the super-spreaders or the TICTF banks?) is still in its infancy. The explanatory variables used to identify these influential spreaders includes typical social network variables like the degree of a bank in the network (the number of connections), and various centrality measures like the a bank's (valued) indegree, (valued) outdegree or betweenness centrality. We will introduce to this economic literature the concept of K-coreness, measured by the K-shell decomposition analysis. Kitsak et al. (2010) show that the node's K-shell index predicts the outcome of spreading more reliably than the degree of the network or any centrality measures. We confirm this result in our simulations of contagion on the interbank network.

There have been some earlier empirical characterizations of the bank network topologies. The first one, an analysis of the Austrian network (Boss et al., 2004) had an incomplete data set and had to resort to certain approximation techniques (like the principle of maximizing the entropy) to make the data more complete. Further, the size of the Austrian interbank network was rather small. We tested our data and small world properties are empirically rejected in our data set. The second study we wish to mention is the analysis of Cont et al (2011) of the Brazilian network. We take the analysis a step further by not only looking at the network topology, but also using network measures to identify those banks that are too interconnected to fail, i.e..

3 Simulating contagion in a bank network

Every bank is a node in the network and every contract between banks is an edge in the network. We consider a multidirected network (gross exposures between banks), instead of a directed network (net exposures between banks) or an undirected one (relations between banks). Consider the matrix of interbank exposures L at the end of a particular period

$$L = \begin{pmatrix} 0 & y_{12} & y_{13} \\ y_{21} & 0 & y_{23} \\ y_{31} & y_{32} & 0 \end{pmatrix}$$

where y_{ij} represents gross claims of bank i on bank j; $y_{ij} = 0$ for $i = j$ as banks don't lend to themselves. To calculate gross claims y_{ij} we sum claims of all maturities of bank i on bank j outstanding at the end of the period. We further decompose those claims into short maturities, y_{ij}^{st}, of up to a month, and long maturities, y_{ij}^{lt}, of more than a month.

We simulate an initial shock (first-round default), and then track how the shock propagates through the interbank network, possibly resulting in knock-on effects, that is, further rounds of contagious defaults. We model the initial shock as a sudden failure of a single bank. Various propagation mechanisms are summarized in Table 1. The insolvency conditions S_i identify insolvent banks, the liquidity conditions L_i identify illiquid banks and the infection conditions I_i identify to which banks the insolvency and liquidity conditions will be applied in the simulations. We will explain these mechanisms one by one, when we introduce combinations of them in our increasingly realistic simulations scenarios (see Panel C).

3.1 Benchmark Scenario 1a: Contagion through Credit Losses

The setup of our benchmark contagion simulation amounts to credit losses depleting bank capital of creditor banks. The initially failing bank defaults on its interbank obligations. Each remaining bank suffers a credit loss equal to its total gross claims on the first-round domino multiplied by the loss-given-default parameter λ. Credit losses deplete the infected creditor banks' capital. If the suffered credit losses exceed capital an infected institution turns insolvent itself and, in turn, defaults on its own interbank obligations. In case such second-round defaults occur, the associated credit losses further deplete the surviving banks' capital and possibly lead to further rounds of insolvencies. In this manner contagion propagates through the system until no more failures occur. Formally, in each round of contagion condition $S1$ determines insolvent institutions.

Table 1: Contagion Simulations

Panel A. Simplified bank balance sheet identity

$$r_i + \sum_{j=1}^{n} y_{ij}^{st} + \sum_{j=1}^{n} y_{ij}^{lt} + s_i + a_i = c_i + \sum_{j=1}^{n} y_{ji}^{st} + \sum_{j=1}^{n} y_{ji}^{lt} + l_i$$

r_i	− excess reserves	c_i	− capital
$\sum_{j=1}^{n} y_{ij}^{st}$	− short-term interbank lending	$\sum_{j=1}^{n} y_{ji}^{st}$	− short-term interbank borrowing
$\sum_{j=1}^{n} y_{ij}^{lt}$	− long-term interbank lending	$\sum_{j=1}^{n} y_{ji}^{lt}$	− long-term interbank borrowing
s_i	− securities		
a_i	− other assets	l_i	− other liabilities

with $n-$ total number of banks,
$\sum_{j=1}^{n} y_{ij} = \sum_{j=1}^{n} y_{ij}^{st} + \sum_{j=1}^{n} y_{ij}^{lt}$,
$\sum_{j=1}^{n} y_{ji} = \sum_{j=1}^{n} y_{ji}^{st} + \sum_{j=1}^{n} y_{ji}^{lt}$

Panel B. Conditions for being insolvent (S), illiquid (L) and infected (I)

$S1$ $\quad c_i < \lambda \sum_{j=1}^{n} \theta_j y_{ij}$

$S2$ $\quad c_i < \lambda \sum_{j=1}^{n} \theta_j y_{ij} + \max\left\{0, \delta\left[\rho \sum_{j=1}^{n} \theta_j (y_{ji}^{st} + y_{ji}^{lt}) - r_i - \sum_{j=1}^{n} (1-\theta_j)(y_{ij}^{st} + y_{ij}^{lt})\right]\right\}$

$S3$ $\quad c_i < \lambda \sum_{j=1}^{n} \theta_j y_{ij} + \max\left\{0, \delta\left[\sum_{j=1}^{n} (y_{ji}^{st} + y_{ji}^{lt}) - r_i - \sum_{j=1}^{n} (1-\theta_j)(y_{ij}^{st} + y_{ij}^{lt})\right]\right\}$

$L1$ $\quad r_i + \sum_{j=1}^{n} (1-\theta_j)(y_{ij}^{st} + y_{ij}^{lt}) + (1 - \frac{\delta}{1+\delta}) s_i < \rho \sum_{j=1}^{n} \theta_j (y_{ji}^{st} + y_{ji}^{lt})$

$L2$ $\quad r_i + \sum_{j=1}^{n} (1-\theta_j)(y_{ij}^{st} + y_{ij}^{lt}) + (1 - \frac{\delta}{1+\delta}) s_i < \sum_{j=1}^{n} (y_{ji}^{st} + y_{ji}^{lt})$

$I1$ $\quad 0 < \lambda \sum_{j=1}^{n} \theta_j y_{ij}$

$I2$ $\quad 0 < \rho \sum_{j=1}^{n} \theta_j (y_{ji}^{st} + y_{ji}^{lt})$

$I3$ $\quad \max[0, (1-\mu)c_i] < \lambda \sum_{j=1}^{n} \theta_j y_{ij} + \max\left\{0, \delta\left[\rho \sum_{j=1}^{n} \theta_j (y_{ji}^{st} + y_{ji}^{lt}) - r_i - \sum_{j=1}^{n} (1-\theta_j)(y_{ij}^{st} + y_{ij}^{lt})\right]\right\}$

$I4$ $\quad (1-\mu) r_i < \rho \sum_{j=1}^{n} \theta_j (y_{ji}^{st} + y_{ji}^{lt})$

where:
$\theta_j = 1$ if bank j has defaulted, and 0 otherwise
λ - loss given default (LGD) on interbank assets
ρ - fraction of lost funding from failed banks that cannot be replaced
δ - fire sale asset haircut: selling assets worth $(1+\delta)$ a bank takes a loss of δ
$(1-\mu)$ - fraction of capital c_i / reserves r_i needed to be destroyed to trigger a run

Panel C. Default rules for different contagion scenarios

Contagion scenario	Default rule
1a: credit loss	$S1$ & $I1$
2a: credit + funding loss	($S2$ *or* $L1$) & ($I1$ *or* $I2$)
3a: credit + funding loss + run on infected	{($S2$ *or* $L1$) & ($I1$ *or* $I2$)} *or* {($S3$ *or* $L2$) & ($I3$ *or* $I4$)}
4a: credit + funding loss + run on all	$S3$ *or* $L2$
2s, 3s, 4s:	same as 2a, 3a, 4a but all $y^{lt} = 0$

Some banks in our dataset enter the simulations in a state of insolvency, that is, with negative capital. Without extra constraints all such banks would default in the second-round of the simulation. We think that a more sensible treatment of such negative-capital banks, given they have not been closed down by the regulator, would be to let them survive unless they are hit by a negative shock. To that end, we combine the solvency condition $S1$ with the infection condition $I1$, requiring a bank to get infected - that is, to suffer non-zero losses in the contagion exercise - before it dies.

3.2 Scenario 2a: Contagion through Credit and Funding Losses

Scenario 2a adds to scenario 1a the problem of funding liquidity losses, as emphasized in the more recent literature. As in scenario 1a, the first-round domino fails and the lenders suffer a credit loss. On top of that, the borrowers suffer a loss of funding previously granted by the first-round domino. Part of that funding can be replaced on the interbank market. the remainder (fraction ρ) erodes bank's liquidity. If liquid assets are insufficient to cover the funding loss, the bank starts a fire sale of securities. The latter sell at a discount relative to their book value resulting in a fire sale haircut. Default occurs if:

- the bank suffers a credit loss ($I1$) OR
- the bank suffers a funding liquidity loss ($I2$)

AND

- combined credit and fire sale losses exceed bank capital ($S2$), OR
- cash raised through the sale of securities is still insufficient to cover the funding loss ($L1$).

In case such second-round defaults occur, the associated credit and funding losses further deplete the surviving banks' capital and liquidity, and possibly lead to further rounds of failures. In this manner contagion propagates through the system until no more failures occur.

Formally, in each round of contagion condition $L1$ determines illiquid institutions. Its right-hand side (RHS) represents an irreplaceable funding loss; its left-hand side (LHS) comprises bank's liquid assets (excess reserves plus interbank claims on surviving banks) and the market value of securities after accounting for the fire sale asset haircut δ. If $LHS < RHS$ the bank is illiquid.

Condition $S2$ determines insolvent institutions. It is similar to condition $S1$, except for the last term inside the *max* function representing fire sale losses. This last term says first, that fire sale losses can't be negative, and second, that positive fire sale losses are equal to the fire sale asset haircut δ on the part of the irreplaceable funding loss (first term in squared brackets) in excess of liquid assets (next two terms in squared brackets).

Similarly to scenario 1a, we require a bank to get infected - that is, to suffer a non-zero credit or funding loss through contagion - before it dies. These infection conditions are represented by conditions $I1$ *or* $I2$. These infection conditions imply that we assume, up till now, that banks do not reassess their relations with still healthy banks as a consequence of a crisis. The network does not, as yet, change endogenously.

3.3 Scenario 3a: Contagion through Credit/Funding Losses and Runs on Infected Banks

Contagion scenario 3a adds one extra feature to scenario 2a (see Table 1) - term $\{(S3 \textit{ or } L2) \ \& \ (I3 \textit{ or } I4)\}$. It says: if a bank is strongly infected (conditions $I3$ *or* $I4$), then it is prone to a run, and to survive, must satisfy stronger conditions for both solvency ($S3$) and liquidity ($L2$) to prevent failure. This strong infection occurs either when combined credit and fire sale losses erode a certain fraction $(1-\mu)$ of bank capital $(I3)^2$, or when funding losses erode a certain fraction $(1-\mu)$ of its liquidity ($I4$). Interbank market participants are generally risk averse and would rather be safe than sorry. In periods of uncertainty and mutual suspicion they might overreact to any negative news and run on infected institutions by not prolonging outstanding credits and withdrawing funds on current accounts, even if these banks are still liquid and solvent. The parameter μ controls the sensitivity of market participants to bad news: higher μ means even small contagious losses make banks vulnerable to a broader run. The structure of the network, that is, reacts to the crisis because banks reconsider their existing links.

The solvency and liquidity conditions $S3$ and $L2$ are visually very similar to, respectively, conditions $S2$ and $L1$. The difference is that a bank prone to a funding liquidity run must have enough capital and liquidity to cover an irreplaceable funding loss equal to its *total interbank obligations*. That intuition explains the absence of fraction ρ in $S3$ and $L2$: none of the lost funds can be replaced in case of a run. It also explains the absence of default indicator θ in $S3$ and $L2$: the loss of funding from both failing and surviving banks must be covered.

[3]

3.4 Scenario 4a: Contagion through Credit/Funding Losses and Runs on All Banks

The initial failure creates a panic-like environment destroying all trust in the banking system, in effect, *contaminating all banks*. Contagion propagates similarly to scenario 3a, but with *all* banks assumed strongly infected from the start. It is our empirical version of liquidity hoarding by all banks.

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[2] Any non-zero loss suffices in case bank capital is negative to start with.

[3] For $\mu = 100\%$ all infected banks are also *strongly* infected.

3.5 Scenarios 2s, 3s, 4s

Interbank crises are a short-term phenomenon, typically lasting for weeks or, at most, months. Within such a short period banks can run on each other by not prolonging/withdrawing short-term, but not long-term funds. The same argument can be extended to the loss of funding from defaulting institutions: in the short run it is only short-term, not long-term funding that is lost. On the contrary, credit losses equally apply to interbank assets of all maturities.

Scenarios 2s, 3s and 4s repeat their respective counterparts 2a, 3a and 4a but taking into account maturity differences of interbank claims. Specifically, each y_{ji}^{lt} mentioned explicitly in conditions $S1-S3$, $L1-L2$, $I1-I4$ of Table 1 is treated as zero. Such treatment allows banks to withdraw only short-term funds from each other. In the rest of the paper we report the simulations with all contracts, but all simulations with only short maturities are available on request and yield very similar results.

3.6 Simulation parameters

$\lambda, \rho, \delta, \mu$ are exogenous parameters. They can take any value desired. In the reported simulations we have assumed them to be equal for all banks. Unless stated otherwise we consider two parameter sets:

1. $\lambda = \rho = \delta = \mu = 50\%$
2. $\lambda = \rho = \delta = \mu = 100\%$

The latter set represents very adverse market conditions, probably close to a truly worst-case scenario:

- loss given default of 100%;[4]

- no replacement of funding losses;

- a 50% loss on securities sale: selling assets worth $(1+\delta) = (1+100\%) = 2$ a bank takes a loss of $\delta = 1$, that is, a 50% loss;

- extreme sensitivity of market participants to bad news: news about losses of any magnitude makes banks vulnerable to a run.

Any other combination of parameters is of course possible, probably slightly more realistic, and available on request, but these simple assumptions performed very well. Although a loss given default of 100% seems exaggerated, we need to take into account we consider immediate contagion, not the ultimate result months or years later after working out all claims in bilateral settlements

[4] The assumption that a bank loses (a large portion of) its total gross claims on the defaulting institution is consistent with the evidence on actual recovery rates. The CBR reports that only 3% of interbank claims on failed institutions were recovered in the process of bank liquidation in the period 2001-2003 (Vedomosti, 2003, N 121 (921)). In other words, loss given default on interbank claims was almost 100%.

or court. For a bank's liquidity and solvency indeed the loss is initially complete. Throughout the simulations we never allow foreign banks to fail, adding some exogenous stability to the Russian banking market. This is in line with reality, where foreign banks were in times of crisis always bailed out by their parents and never failed. We do, however, allow foreign banks to run on domestic banks: claims on and debts to foreign banks enter the calculation of domestic banks' interbank positions. This is also in line with reality.

In each period we let every bank perform the role of the exogenously failing initial domino and track the resulting contagion effects as defined above. We calculate two measures of contagion excluding the initial domino: the percentage of failed banks; and the share of failed assets in system-wide assets. For each month for each initially failed bank we get 28 estimates of contagion: 7 scenarios * 2 parameter sets * 2 contagion measures. The method can of course very easily accommodate any other combination of parameters or even a parameter grid search to expand the set of results, but it seems to us that the direction of the results is abundantly clear with the current set of results. All other combinations of scenarios and parameters can be easily implemented and are available on request.

One can argue that the haircut should be endogenised. Indeed the haircut in a given round of the simulations is endogenous to the number of failing banks and the share of lost assets in previous rounds. This problem of endogenous haricuts has a unique solution, which was provided by Eisenberg and Noe (2001) and applied by Müller (2006). We find however that even the relatively high constant haircut of 50% we apply has only minor effects on the simulation outcome. We also think we have reasons te believe that a truly endogenous haircut will only reinforce the results. Indeed, if we make the haircut an increasing function of the number of failing banks and/or the share of last assets, we arrive at relatively lower haircuts in calm periods and higher haircuts in crisis periods, nomatter the precise functional form. This further magnifies the differences between these two periods in the simulations results. Introducing this endogenous haircut would therefore leave our analysis exposed to the criticism that our results are due to the specific functional form of this endogenization. Since we are able to identify the crisis periods very accurately with the simplifying assumption of a constant haircut, and since these results can only further improve by the endogenization of haircuts, we choose to present results with constant haircuts.

4 Russian Interbank Market

4.1 Data Description

Mobile and Banksrate.ru, two highly respected private financial information agencies, provided us with, respectively, monthly bank balances and monthly reports "On Interbank Loans and Deposits" (official form's code 0409501) for the period 1998m7 - 2004m10.[5] Both types of information are a part of standard disclosure requirements and must be supplied to the regulator on a monthly basis. The latter report provides information on banks' gross interbank positions split by counterparty, enabling us to reconstruct the exact matrix of interbank exposures at the end of each month (for further details see Appendix 9.1). Balance sheets of foreign banks and off-balance-sheet positions are not available.

In our contagion exercise we use five items from bank balance sheets:

1. excess reserves, r_i, defined as correspondent accounts with the Bank of Russia plus correspondent accounts with other banks

2. securities, s_i, defined as government plus non-government securities

3. capital, c_i

4. interbank assets, $\sum_{j=1}^{n} y_{ij}$

5. interbank liabilities, $\sum_{j=1}^{n} y_{ji}$

Figures 1 and 2 present the distributions of those five variables over time. All variables are expressed as a percentage of total assets; each observation represents a measure for a single bank in a specific month.

By analogy with the spreading of contagious disease, we can think of excess reserves, securities and capital as characterizing the strength of a bank's immune system: the higher those ratios are, the less likely a bank is to succumb to contagion and die. In particular, a high capital buffer allows to absorb large credit and fire sale losses, while a high liquidity buffer (reserves + securities) protects against funding losses and runs.

Figure 1 shows that in all years, average (median) capital buffers stay within a comfortable range of 23-25% (resp. 18-22%) of total assets. The distribution tends to narrow down: over time we observe fewer banks with very low or very high capital ratios. Remarkably, in every single year there operate a few institutions with *negative* capital; in our contagion exercise losses of any magnitude would lead to default of those institutions.

Liquidity buffers are, on average, also adequate. While the average share of securities in total assets decreases from 19% in 1998 to 13% in 2004, the average share of reserves first rises from 11% in 1998 to 18% in 2000-2001, and then falls to 14% in 2004. As a result average liquidity buffers (reserves and securities combined) are somewhat lower in 1998 and 2004 compared to the years in between.[6] In all years there are banks with both near zero as well as near 100% liquidity buffers.

[5] For more information on the data providers see their respective websites at www.mobile.ru and www.banks-rate.ru. Karas and Schoors (2005) provide a detailed description of the Mobile database.

[6] The medians follow the same pattern.

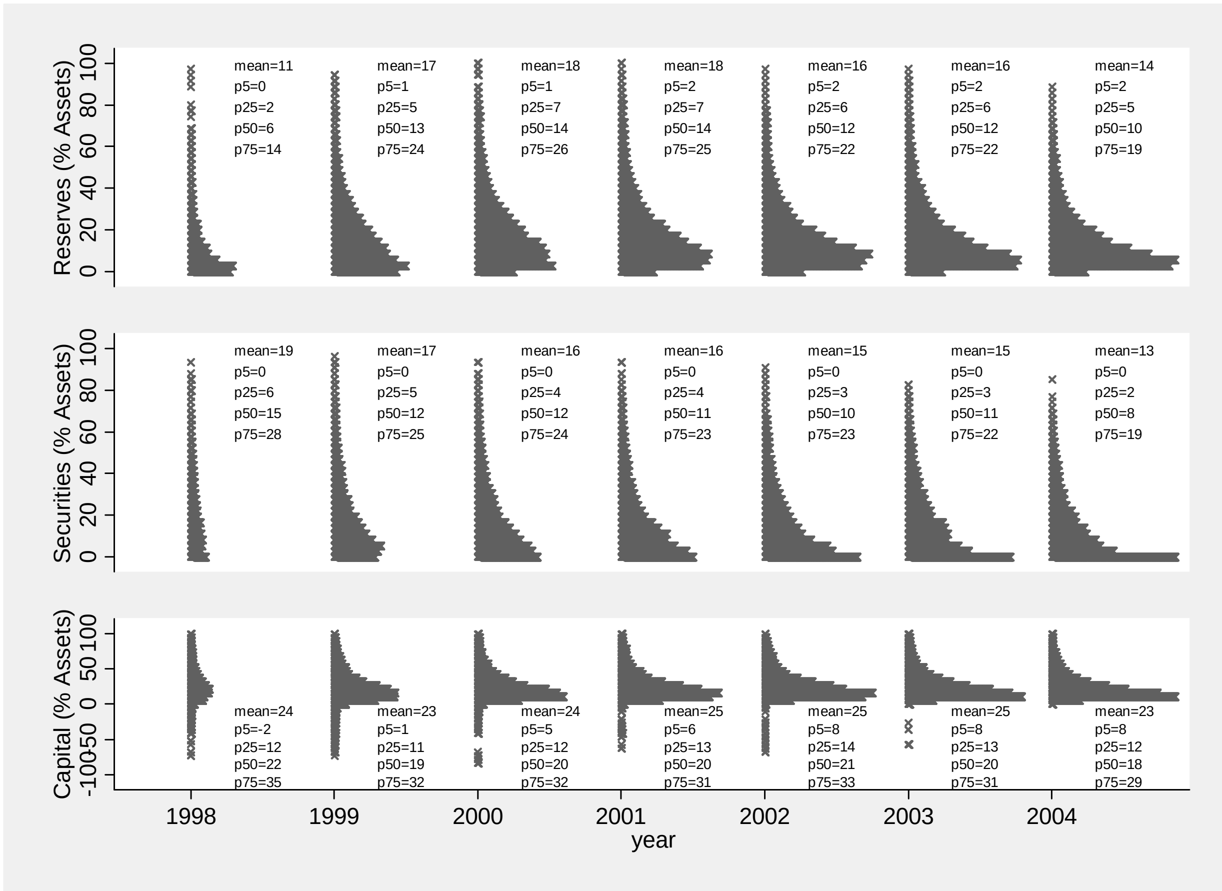

Figure 1: Summary Statistics: Reserves, Securities & Capital

Next to the strength of banks' immune system, the spread of contagion is also determined by the size and structure of banks' bilateral exposures. As shown in Figure 2 most Russian banks have a small to moderate exposure to the interbank market of up to 10% of total assets; yet some banks have an exposure in excess off 50%. The average Russian bank is a net borrower on the interbank market : the average share of interbank assets in total assets fluctuates around 4-5%, while the average share of interbank obligations varies from 6 to 8%. The average net liability position has remained rather stable over time. Though average capital and liquidity buffers seem large in comparison with average interbank positions, contagion can still find its way through banks with low buffers and/or large exposures.

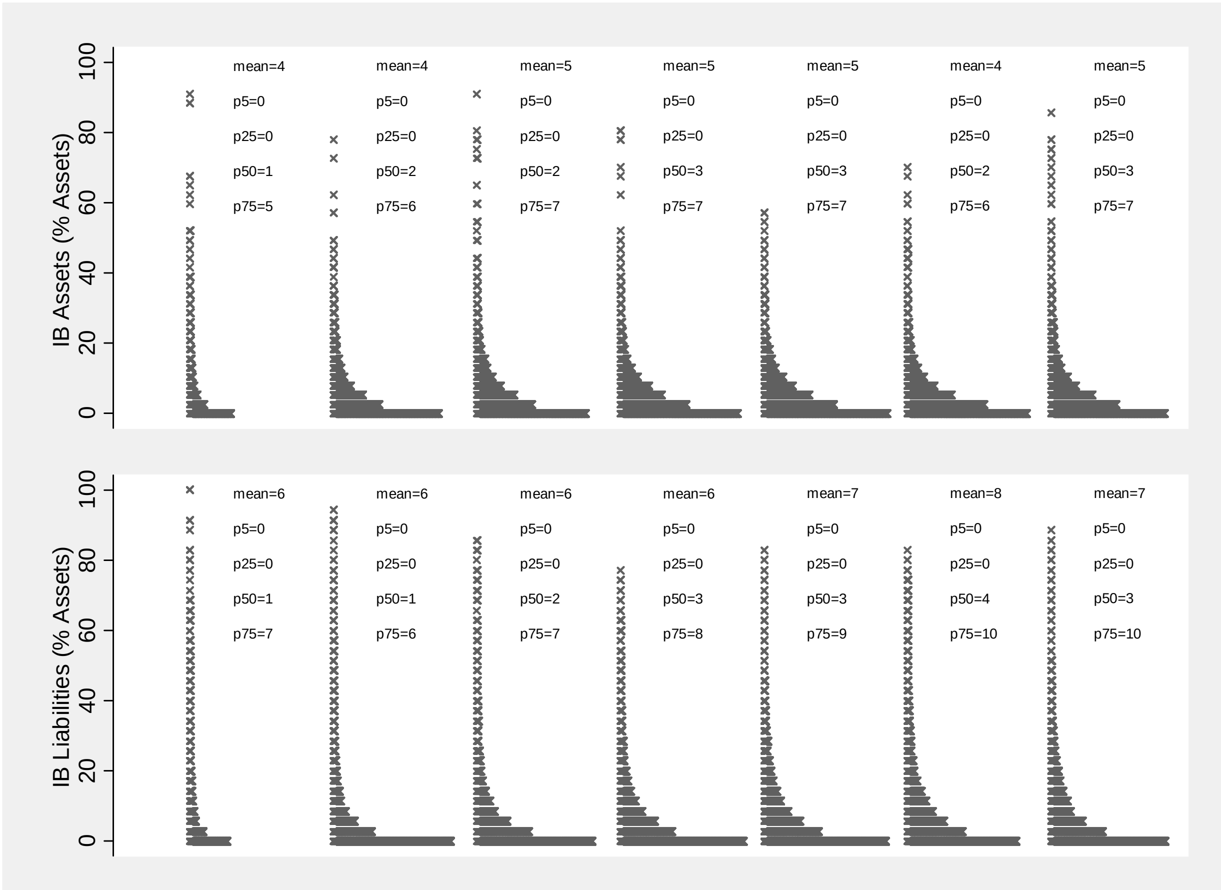

Figure 2: Summary Statistics: Interbank Assets & Liabilities

4.2 Market Structure

This section discusses the interbank market structure. In each period we assign banks to one of the three groups:

1. domestic big B - top 40 banks in terms of total assets
2. domestic small S - all remaining domestic banks
3. foreign F

We further compose a matrix G of group-wise exposures split by maturity

$$G = \begin{pmatrix} SS^{st}, SS^{lt} & SB^{st}, SB^{lt} & SF^{st}, SF^{lt} \\ BS^{st}, BS^{lt} & BB^{st}, BB^{lt} & BF^{st}, BF^{lt} \\ FS^{st}, FS^{lt} & FB^{st}, FB^{lt} & FF - unknown \end{pmatrix}$$

where BB^{st} (BB^{lt}) represents short-term (long-term) loans from big domestic banks to other big domestic banks, SB - from small to big, FB - from foreign to big, etc. Figures 3 - 6 plot those group-wise exposures over time: Figures 3 and 5 report interactions between domestic and foreign banks (FS, FB, SF, BF); Figures 4 and 6 focus on interactions between domestic banks (SS, SB, BS, BB). On the vertical axis we indicate the time period (month) and the number of domestic banks active on the interbank market during that period.

The length of each bar represents total claims outstanding at the end of the respective month between domestic and foreign banks (Figure 3) and between domestic banks (Figure 4). In both figures bar lengths considerably increase over the sample period: almost 7-fold in Figure 3 and 12-fold in Figure 4. However, while the latter increase is fairly gradual over time, the former is largely concentrated in the first 7 and the last 20 months of the sample period. All claims combined (not shown) rise at a pace comparable to that of nominal GDP (claims rise by a factor of 7.4 versus 6.5 for GDP).[7] Now compare the lengths of bars across Figures 3 and 4. Clearly, total outstanding claims involving a foreign counterparty have always been a factor of 2 to 5 larger than those involving only domestic banks, indicating the crucial stabilizing role of foreign banks in providing interbank market funding to the Russian banking system, at least in 2004 and 2008. In 2008, the shock in foreign interbank markets turned this dependence on foreign banks into a weakness, rather than a strength and exposed the Russian banking system to a sudden stop problem.

The differently colored components of each bar in Figures 3 and 5 clarify what types of foreign transactions are particularly wide-spread. Focusing on Figure 5, where interbank claims are presented as shares of total, the first 4 colored components counting from the left, from white to black, represent loans *from* foreign banks, FS and FB. Together they visibly dominate the remaining 4 components representing loans *to* foreign banks, SF and BF. In turn, of all loans *from* foreign banks the overwhelmingly dominant share has at least a month to maturity (FS^{lt} and FB^{lt}), of which the major part is absorbed by big banks (FB^{lt}). In contrast, loans *to* foreign banks largely have short-term nature: a particularly large component is BF^{st}, the second color counting from the right. Overall, the prevalence of dark colors in Figure 5 highlights that most of cross-border interbank activity is performed by the 40 biggest domestic banks. The only notable exception is long-term lending FS^{lt} to small banks, the second color counting from the left. All this again clearly illustrates the dependence of the Russian interbank market on foreign wholesale funding.

While most of cross-border interaction falls on big Russian banks, purely domestic activity is far less concentrated. The two most right components in Figure 6, representing transactions between

[7] Source: Rosstat

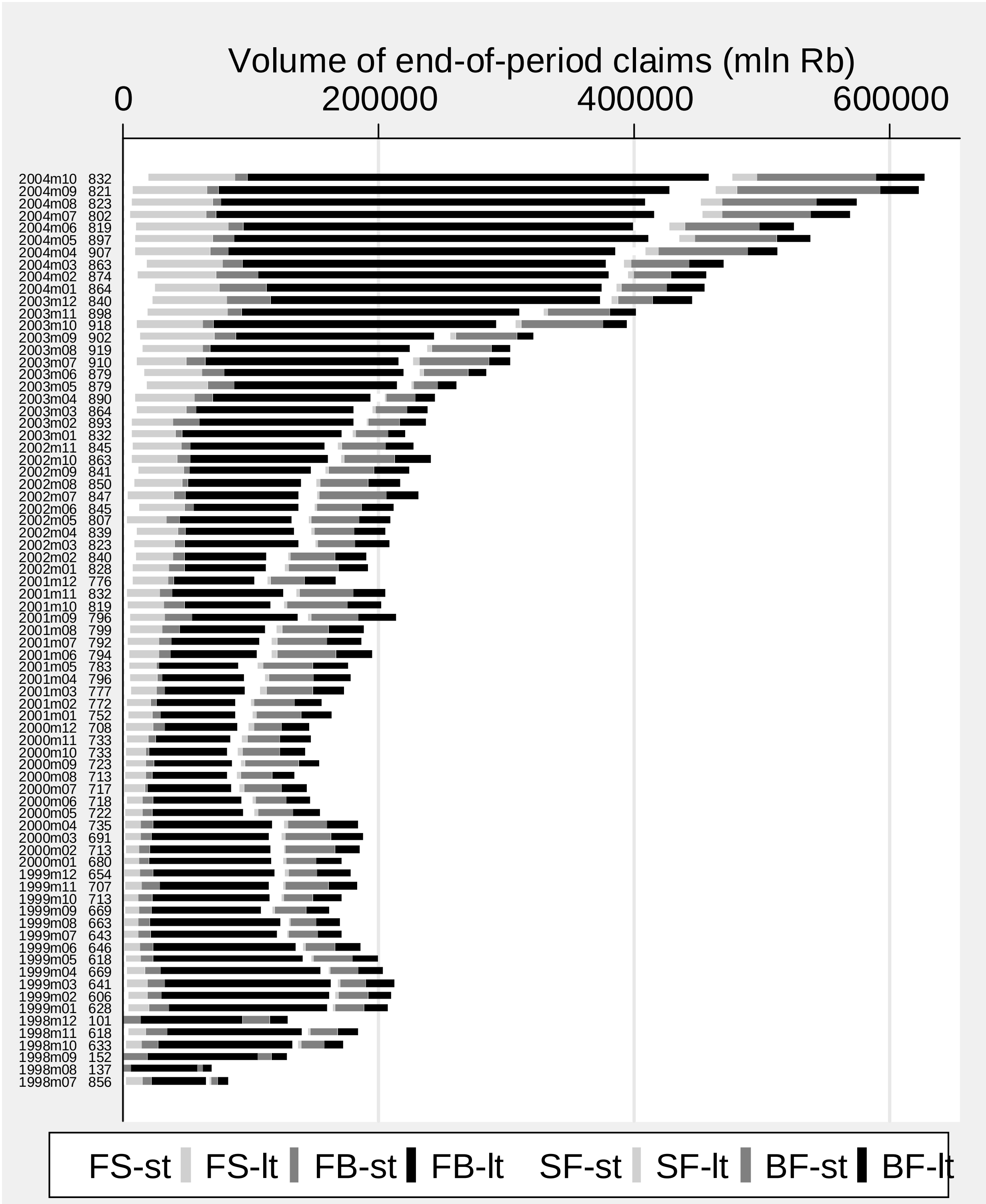

Figure 3: Foreign - Domestic Interbank Interactions Split by Maturity

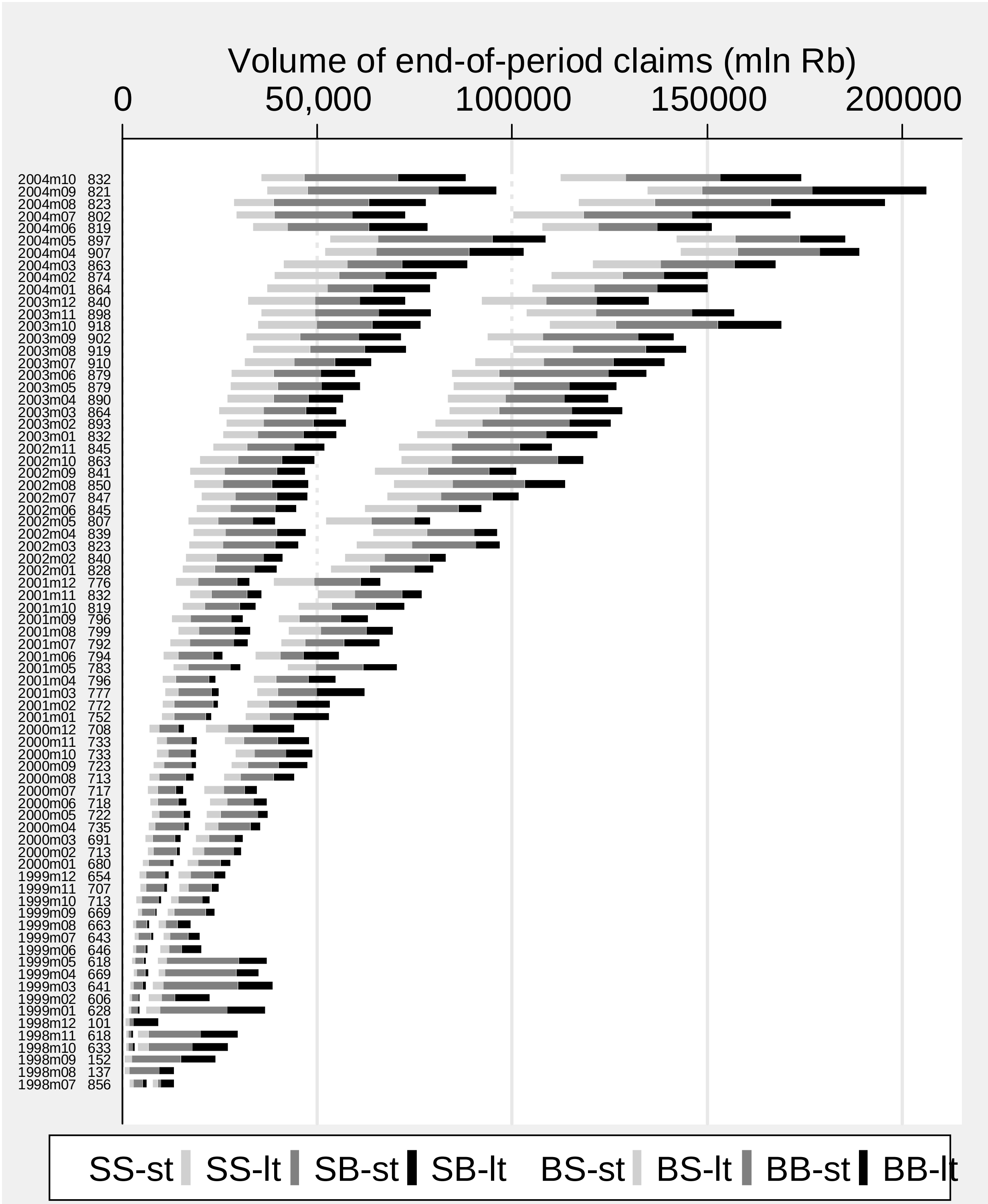

Figure 4: Small - Big Domestic Interbank Interactions Split by Maturity

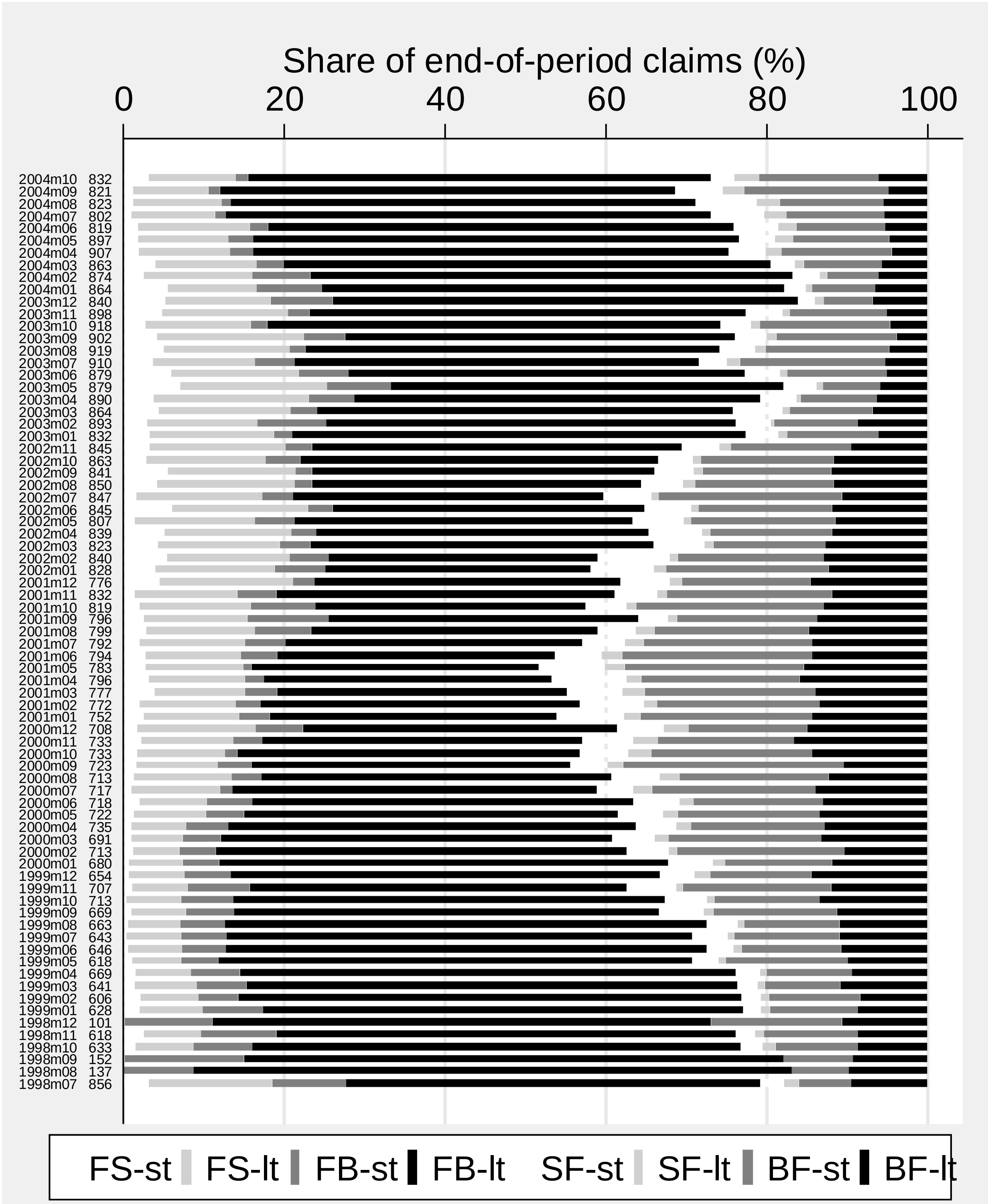

Figure 5: Foreign - Domestic Interbank Interactions Split by Maturity

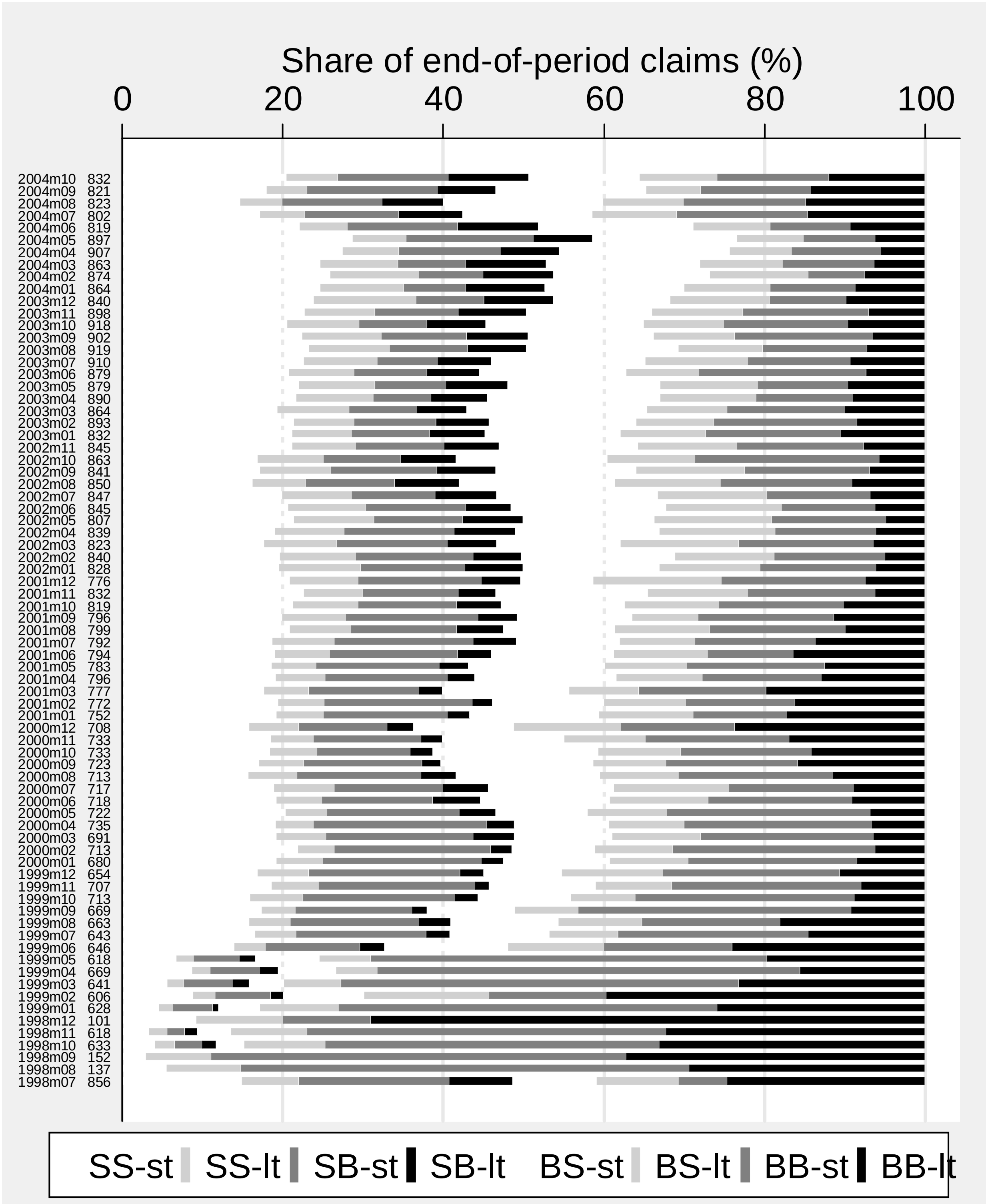

Figure 6: Small - Big Domestic Interbank Interactions Split by Maturity

big banks (BB^{st}, BB^{lt}), are only dominant in the few months of low interbank market activity following the August 1998 crisis. Starting from year 2000 the other components (BS, SB, SS) are roughly on par with BB. Further, loans originating from small banks (the left 4 colors from white to black) are generally comparable in magnitude to loans originating from big banks (the right 4 colors, again from white to black). In terms of maturity short-term claims prevail in all categories.

4.3 Interbank Market Crises

The 2004 'mini-crisis' started with an unexpected failure of a *single* bank. The bank was fairly small, and was not an important interbank market player; its failure occurred at the time when Russian economy (including its banking system) was in good shape. Yet that single failure caused panic and a near collapse of the whole interbank market.

In May 2004 the Central Bank of Russia (CBR) deprived Sodbusinessbank of its license on accusation of money-laundering (the first case of this kind in Russia). A few days later the head of the Federal Service for Financial Monitoring (FSFM) Mr. Zubkov announced that his Service suspected about a dozen banks in money laundering and sponsorship of terrorism, without naming the 'dirty dozen'. Several inconsistent 'black lists' began circulating the banking community as bankers tried to guess which banks were suspected by the FSFM. Mutual suspicion led to a drying up of liquidity on the interbank market, putting pressure on the hundreds of smaller banks that are highly dependent on it. The crisis of confidence provoked runs on several large banks among which were Guta Bank and Alfa Bank. Being severely hit by the liquidity shock and abrupt withdrawal of a number of large depositors, Guta Bank found itself on the edge of bankruptcy and was acquired by the state-owned Vneshtorgbank at a symbolic price.

The 2004 turmoil, taking place during a favorable macroeconomic environment, contrasts sharply with the crisis of 1998, which resulted from a fundamental systemic shock directly jeopardizing the solvency of multiple banks. The government's desperate need for money in the run-up to the 1996 presidential elections led to very high yields on treasury bills (GKOs). In the beginning of 1996 the average lending rate on loans to the real economy was 60% per annum, while the yield on GKOs was around 100% per annum. Moreover, incomes from GKO investment were tax deductible. In the second half of 1996 Russian banks began borrowing actively on foreign markets (currency loans from foreign banks and Eurobonds). The huge difference between domestic and foreign interest rates in combination with relatively stable ruble exchange rate, guaranteed by the ruble corridor policy (a crawling currency band), ensured huge profits. When the GKO market was opened to foreigners in 1997, the desire of foreign investors to hedge their ruble investments was met by Russian counterparts, who took short positions in forward contracts on foreign currency. The Russian banks, involved in this trade, carried a huge amount of fundamentally uncovered currency risk. In the beginning of 1998 the share of foreign currency denominated liabilities significantly exceeded ruble denominated liabilities. In a vain attempt to reduce the currency mismatch in their books, banks began extending foreign currency denominated loans to domestic borrowers. In fact, by shifting currency risk to their borrowers banks substituted it by credit risk, because after the ruble devaluation most of the borrowers defaulted.

The Asian crisis and dwindling yields on GKOs made Russian government debt securities less attractive to foreigners and provoked capital outflows. Protecting the ruble from devaluation, the CBR lost the lion's share of its international reserves. At the same time the Russian government faced problems to roll over its GKO debt. In August 1998 the CBR's exchange rate policy became untenable. Although GKO yields soared to 100% per annum and more, banks were liquidating their positions. On 17 August 1998, Russia abandoned its exchange rate regime, defaulted on its domestic public debt and declared a moratorium on all private foreign liabilities, which was equivalent to an outright default. The Russian bank sector was hit severely by the uncovered forward contracts on foreign currency, the government default on GKOs and the subsequent bank runs (Perotti, 2002). The crisis completely paralyzed the interbank market. The recovery took more than a year.

5 Simulation Results

5.1 Scenario 1a: Contagion through Credit Losses

Figure 7 reports the results of our contagion simulations for scenario 1a with $\lambda = 100\%$. The length of each bar represents *the frequency* of contagion - the number of first-round dominos that generate non-zero contagion in a particular month. That number can range from a minimum of zero to a maximum of all institutions active on the interbank market in the corresponding month; the latter is reported on the vertical axis next to the time period.

The colors in Figure 7 represent *the damage* done by contagion, measured as a percentage of failed assets (excluding the initial domino) in system-wide assets. We assign all instances of contagion into four categories based on their damage: from minor damage of up to 1% of system-wide assets (light gray) to substantial damage of above 10% (black). The left *black* number next to each bar signifies the maximal simulated damage, that is, the worst-case scenario. The right *gray* number indicates the percentage of system-wide assets that belongs to initially *weak nodes*, here defined as banks with negative capital. The latter are a particularly easy target for contagion: given their initially negative capital even minor losses result in their failure. Both numbers are rounded to a full percentage point.

The results of this simulation show very little signs of trouble, just like the early contagion literature failed to predict the 2007-2012 problems with models solely based on credit losses and capital buffers. On average the frequency and the damage of contagion are very low: only about 2% of initial failures lead to contagion and even the worst-case damage rarely affects more than

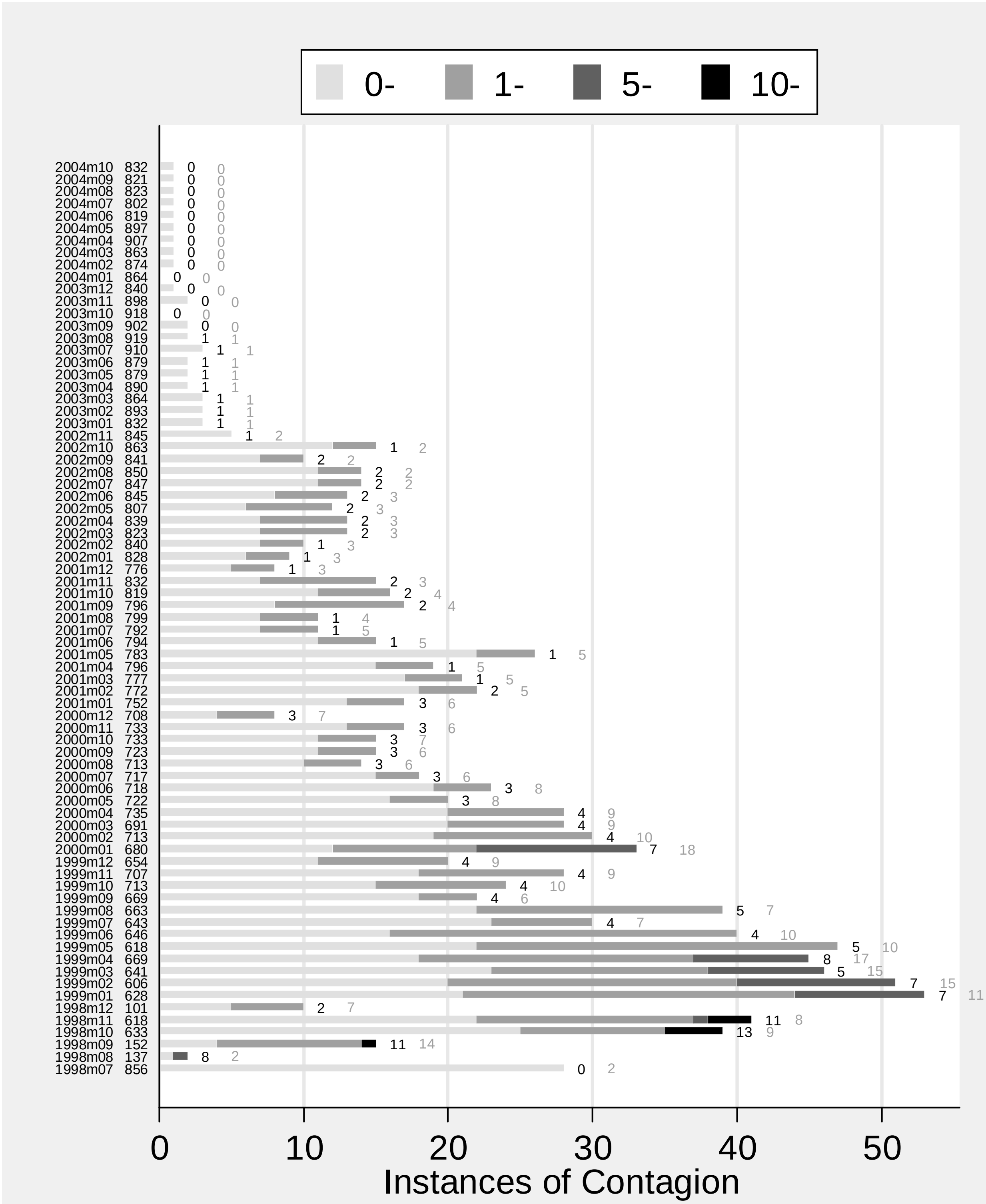

Figure 7: Percentage of Failed Assets (Scenario 1a, $\lambda = \rho = \delta = \mu = 100\%$)

5% of system-wide assets. Interestingly the model does seem to capture the timing, though not the severity, of the 1998 crisis. Indeed both the frequency and the inflicted damage of contagion are comparatively pronounced during and right after the August 1998 crisis. In these months we observe that 6-7% of the initial failures lead to contagion and several of the contagious banks inflict serious damage on the system, as shown by the dark colors on the bars in these months. The worst-case scenario damage hovers around or even above 10% during and in the immediate aftermath of the 1998 crisis. On the other hand, we also observe that the frequency and the damage fall gradually fall to zero over time and remain absolutely flat during the sever 2004 crisis. In addition these simulation give no indication of the coming August 1998 melt-down: the frequency and the damage are remarkably low in July 1998.

These results are largely driven by the weakness of some nodes in the network. Indeed, when we compare the simulation results from the very adverse environment parameter set (see Figure 7) to the ones from the more moderate parameter set (see Figure 8), we see that the parameters (in this scenario largely the loss given default λ) do not seem to affect the results much at all in terms of frequency of damage inflicted by contagion, suggesting that most of the action in the results comes from *weak nodes* that succumb to contagion regardless of the magnitude of the loss. There are indeed only a few occasions where the, in the worst case scenario, there are more failing banks than weak banks (the black number on the bar exceeds the gray number), showing beyond doubt that contagion has the potential to kill some banks with positive capital buffers. Still, most worst-case scenarios exhibit the opposite pattern, signifying that the contagion simulated in this way is not potent enough even to kill off all the weak nodes in the network. Turning our attention to the number of failed banks in Figures 10/9, we observe the inflicted damage is substantially lower than in our previous result figures focusing at the share of assets lost (Figures 7/8), indicating that in this scenario the damage, if any, mostly comes from a few failing big banks rather than many small ones.

5.2 Scenario 2a: Contagion through Credit and Funding Losses

We know enrich our analysis with funding liquidity losses that run over the network. We will from now on show only one figure with results, namely the figure showing failed assets for the extreme parameter set. The other figures, equivalent with the ones of the previous section, are readily available on request. Figure 11 replicates Figure 7 for scenario 2a with $\lambda = \rho = \delta = \mu = 100\%$.

Results are very comparable to the previous scenario. The main difference seems to be that the inclusion of funding liquidity losses improves the ability of our simulation to capture the severity of the 1998 meltdown. Indeed, during and after the 1998 crisis there are about four times as many instances of contagion and the damage inflicted by contagion is much more severe as indicated by the size of the black bars in the figure. But the 2004 crisis still passes below the radar of our

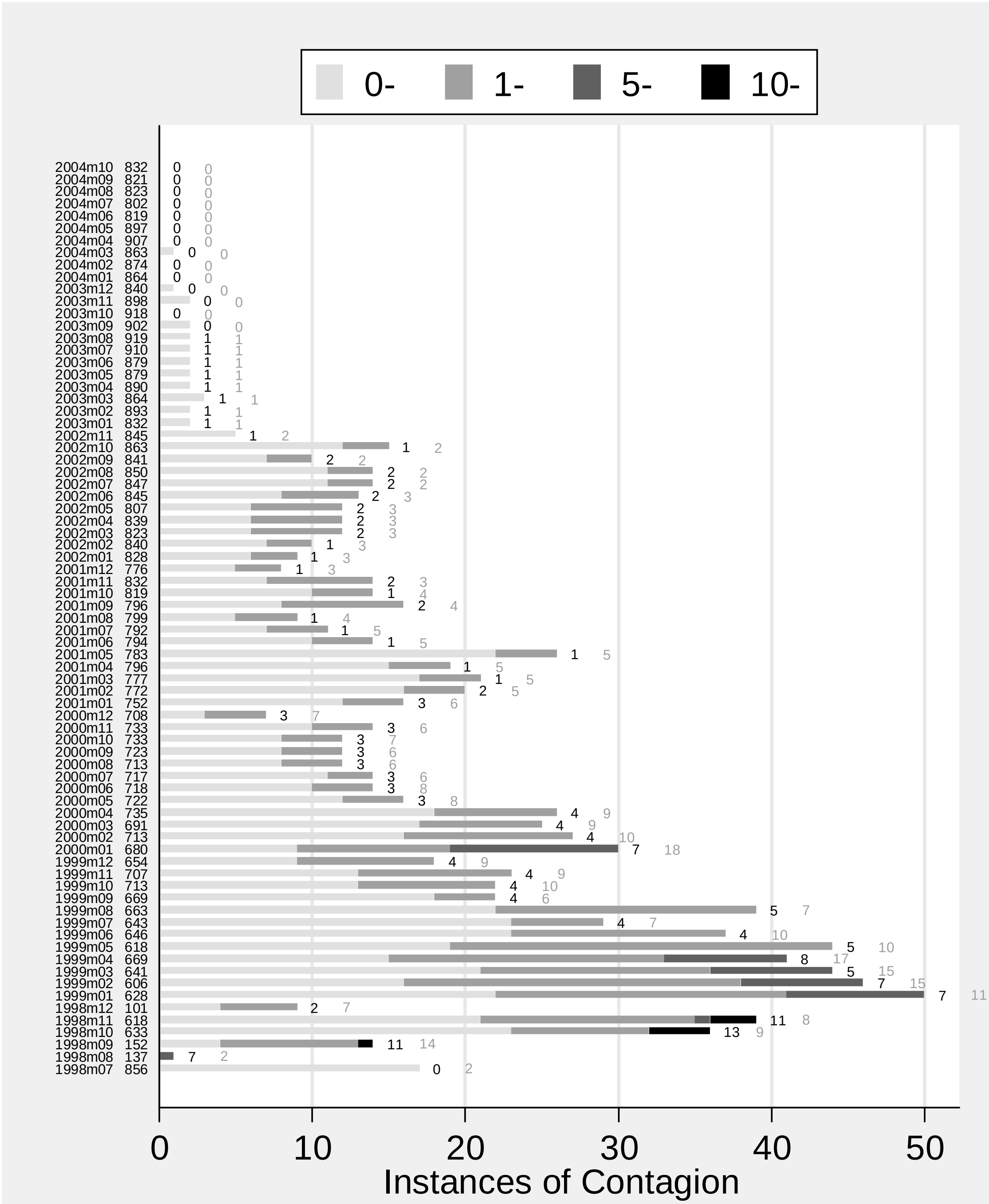

Figure 8: Percentage of Failed Assets (Scenario 1a, $\lambda = \rho = \delta = \mu = 50\%$)

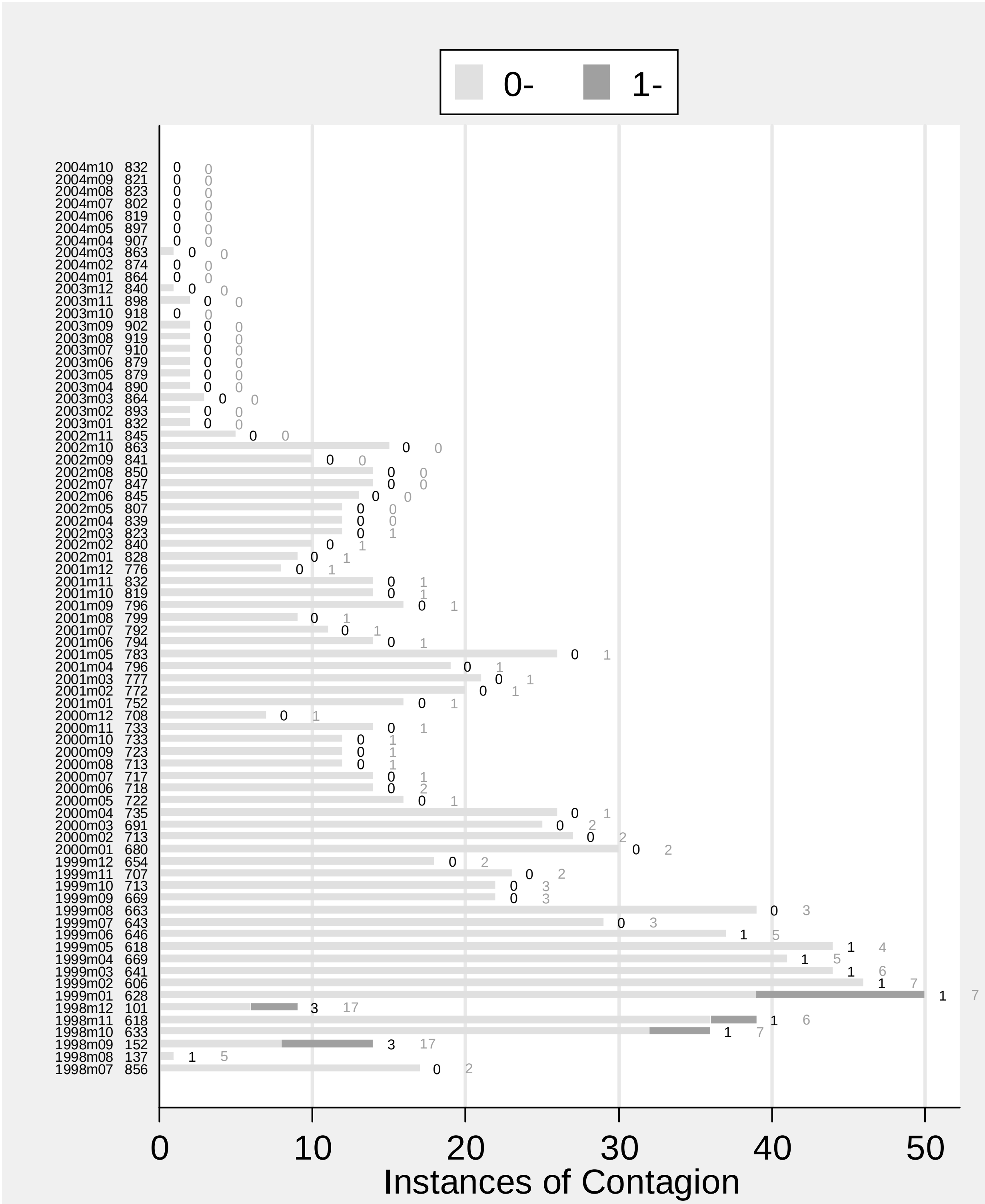

Figure 9: Percentage of Failed Banks (Scenario 1a, $\lambda = \rho = \delta = \mu = 50\%$)

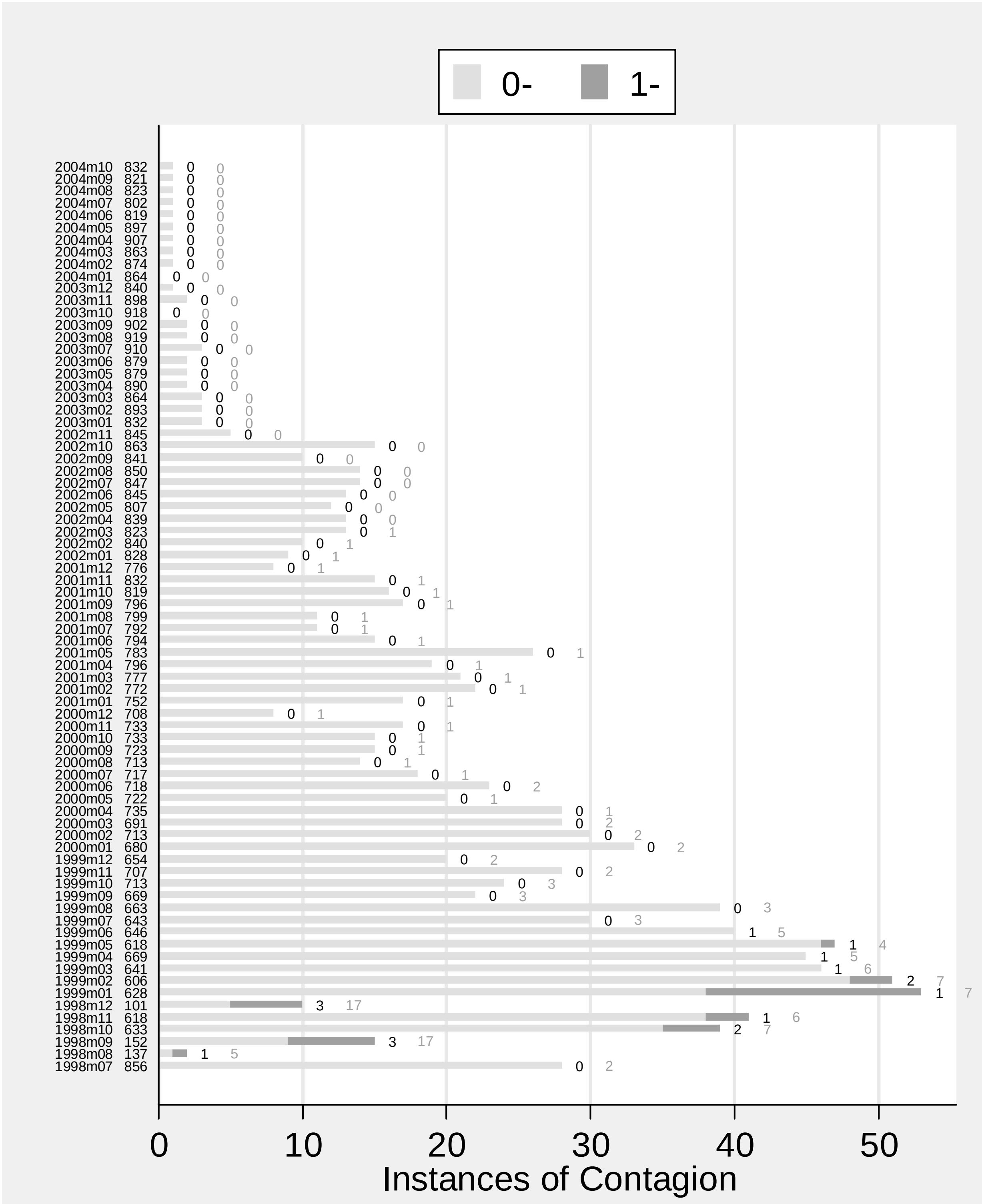

Figure 10: Percentage of Failed Banks (Scenario 1a, $\lambda = \rho = \delta = \mu = 100\%$)

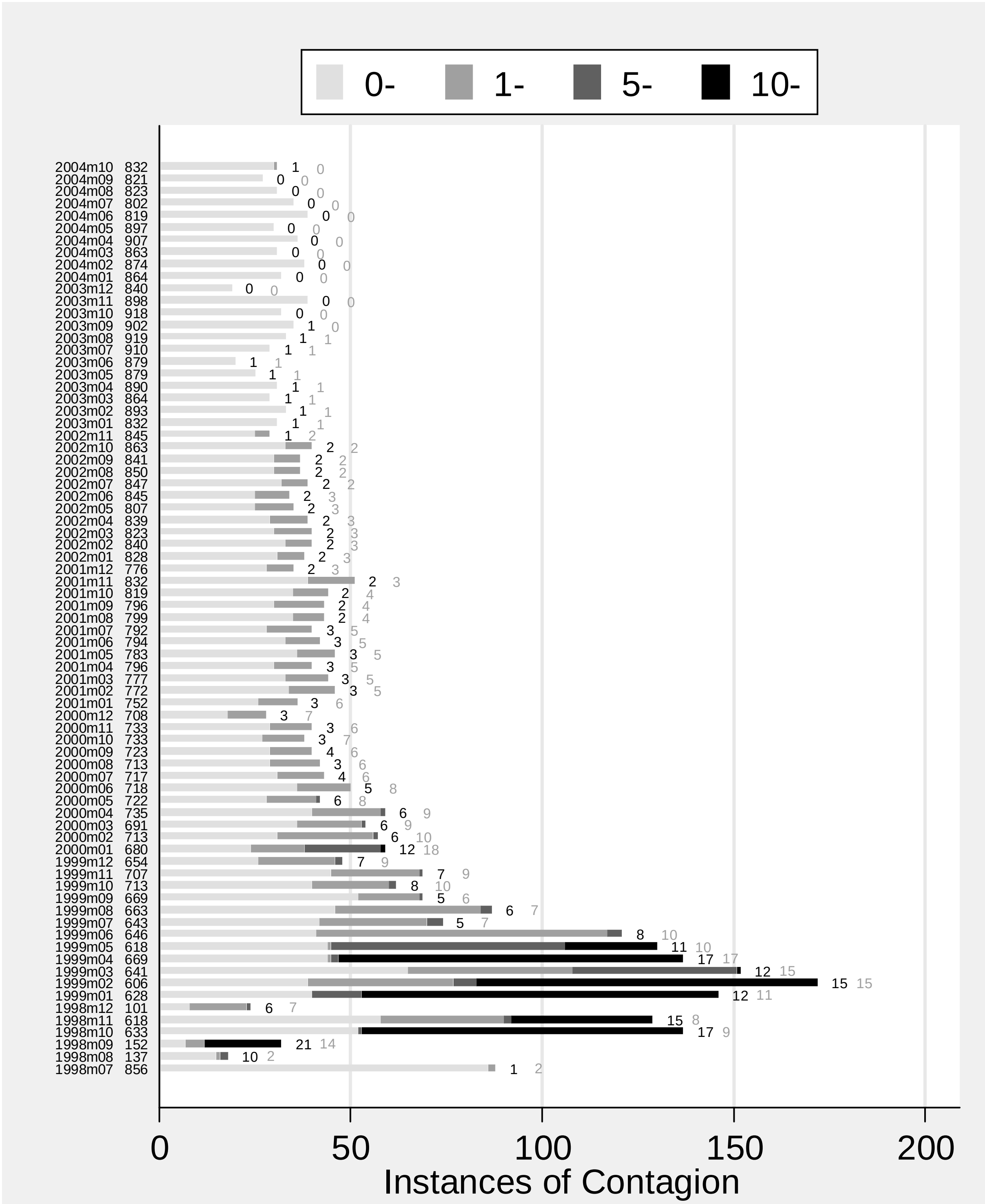

Figure 11: Percentage of Failed Assets (Scenario 2a, $\lambda = \rho = \delta = \mu = 100\%$)

simulations, suggesting that an important transmission channel of interbank market contagion is still missing, though we allow funding liquidity losses.

5.3 Scenario 3a: Contagion through Credit/Funding Losses and Runs on Infected Banks

In scenario 3a we make the structure of the network endogenous, by enriching our previous simulation with the possibility of rational liquidity runs: If a bank is relatively strongly infected by credit or liquidity losses, then it is prone to a liquidity run by others, and to survive, they must have sufficient capital and liquidity to cover an irreplaceable funding loss equal to its *total interbank obligations*. We essentially assume that banks run on infected banks, which seems to be what happened in 2008, 2010 and 2011 in European banking markets. Figure 12 reports our results for scenario 3a with $\lambda = \rho = \delta = \mu = 100\%$. Its layout is similar to Figure 11 with the exception that the initially weak nodes here consist of both insolvent and illiquid banks. We define banks as initially illiquid if their interbank liabilities exceed their liquid assets; the latter consist of reserves, securities and interbank assets.

There are two really striking observations. First of all, the severity of the 1998 crisis is now much better captured, with up to 300 instances of contagion and huge proportions of severe inflicted damage (the black parts of the bars). Second, and probably most important, the 2004 crisis is on the radar screen too now, with even more instances of contagion and higher inflicted damage of the system. Also, even in calm times, there are always at least some instances of possible contagion. These very accurate capturing of reality seems to suggest that the modeling of liquidity runs is crucial to understanding and simulating interbank market instability.

5.4 Scenario 4a: Contagion through Credit/Funding Losses and Runs on All Banks

Figure **??** replicates Figure 12 for scenario 4a with $\lambda = \rho = \delta = \mu = 100\%$. The only difference is that we assume that banks run on each other in any case, whether there is a considerable infection or not. It is, in effect, our way of simulating the impact of a completely blind liquidity hoarding on the interbank market. Not surprisingly, the lion's share of the banking system now succumbs to contagion in most any time period and the interbank market essentially ceases to exist, which possible makes these results less interesting for understanding or anticipating interbank market instability. The results are available on request, but not shown here to economize on space.

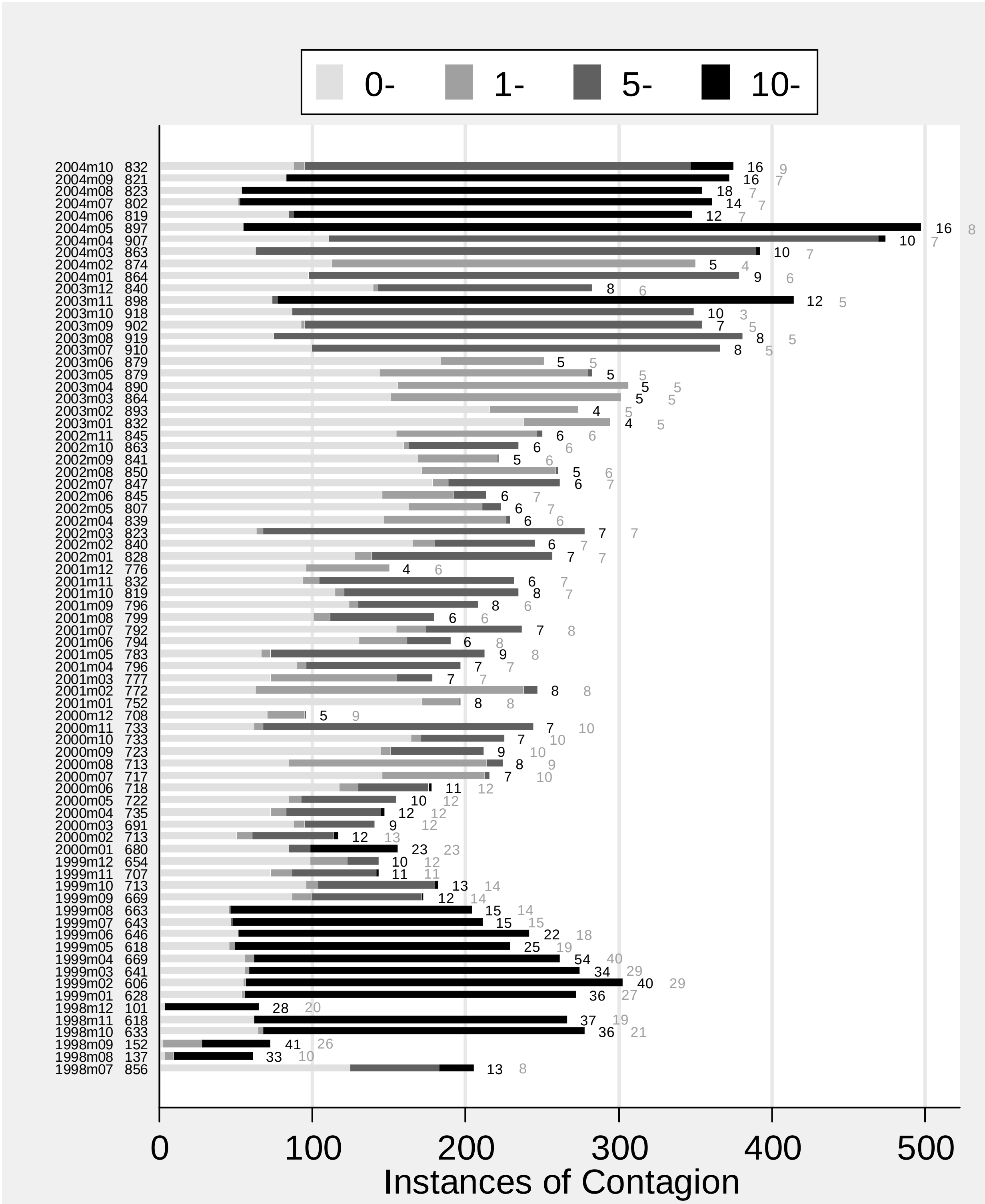

Figure 12: Percentage of Failed Assets (Scenario 3a, $\lambda = \rho = \delta = \mu = 100\%$)

6 Are the influential spreaders of contagion Too Big To Fail or Too Interconnected To Fail?

We view the interbank market as a network. The nodes represent banks and the links (arcs) represent interbank exposures. The degree of a node is the number of connections it has to other nodes. The conventional wisdom in the literature is that the centrality of a node in the network is a good predictor for the node's potential to spread contagion. Kitsak et. al. (2010) challenge that wisdom for a variety of social networks. Kitsak et al. (2010) show that the node's K-shell index, which is the result from a K-core decomposition analysis, predicts the outcome of spreading more reliably than the degree of the network or any centrality measures. We introduce this concept of K-coreness to the banking literature.

We run regressions of the form:

$$C_{it} = \alpha + \beta' Bank_{it} + \lambda_t + \varepsilon_{it} \tag{1}$$

where $i = 1, ..., N$ and $t = 1, ..., T$. N is the number of domestic banks active on the interbank market. The panel is unbalanced, so T, the number of observations per bank, varies across institutions. Time dummies, λ_t, control for macroeconomic and banking sector developments common across banks.

The left-hand side variable, C_{it}, is a measure of contagion produced by the first-round failure of bank i in period t. We employ various contagion measures corresponding to different scenarios presented in section 3. As all those measures are censored at zero for a substantial fraction of banks, we opt for the Tobit model. $Bank_{it}$ represents a vector of bank-specific variables hypothesized to determine bank ability to initiate contagion. Those variables include size (measured as bank assets divided by system-wide assets) as well as a range of descriptors of bank's relative position in the interbank network, namely several centrality indices and an index of *coreness*. Defaulting top debtors (lenders) are likely to produce most contagion: they deliver major credit (resp. funding) losses and infect a large number of counterparties on their liability (resp. asset) side. To capture this spreading capacity we employ five centrality indices (see Table 2). All indices consider transactions between domestic banks only, and are computed for each month separately; all indices range from 0 to 1.

Next to centrality indices we compute an index of coreness, K-shell index. Figure 13 illustrates the procedure. For each month we start by removing all nodes with degree=1. After removing all the nodes with degree=1, some nodes may be left with one link, so we continue pruning the system iteratively until there is no node left with degree=1 in the network. The removed nodes, along with the corresponding links, are assigned a K-shell index of 1. In a similar fashion, we iteratively remove the next K-shell equal to 2, and continue removing higher K-shells until all nodes are removed. As

Table 2: Centrality Indices

Index	Formula	Description
Valued Outdegree	$0 \leq VO_i = \frac{\sum_{j=1}^{n} y_{ij}}{\text{System-wide Assets}} \leq 1$	bank share in system-wide interbank assets
Valued Indegree	$0 \leq VI_i = \frac{\sum_{j=1}^{n} y_{ji}}{\text{System-wide Liabilities}} \leq 1$	bank share in system-wide interbank liabilities
Non-valued Outdegree	$0 \leq NO_i = \frac{\sum_{j=1}^{n}(y_{ij} > 0)}{n-1} \leq 1$	% of market participants a bank has as counterparties on its asset side
Non-valued Indegree	$0 \leq NI_i = \frac{\sum_{j=1}^{n}(y_{ji} > 0)}{n-1} \leq 1$	% of market participants a bank has as counterparties on its liability side
Betweenness Centrality	see Miura (2011) whose Stata Graph Library we use	% of shortest paths linking institutions other than bank i passing through bank i

where $y_{ij}-$ gross claims of bank i on bank j
$(y_{ij} > 0)$ evaluates to 1 if bank i has claims on bank j; and 0 otherwise
$(n-1)-$ max number of links a bank can have

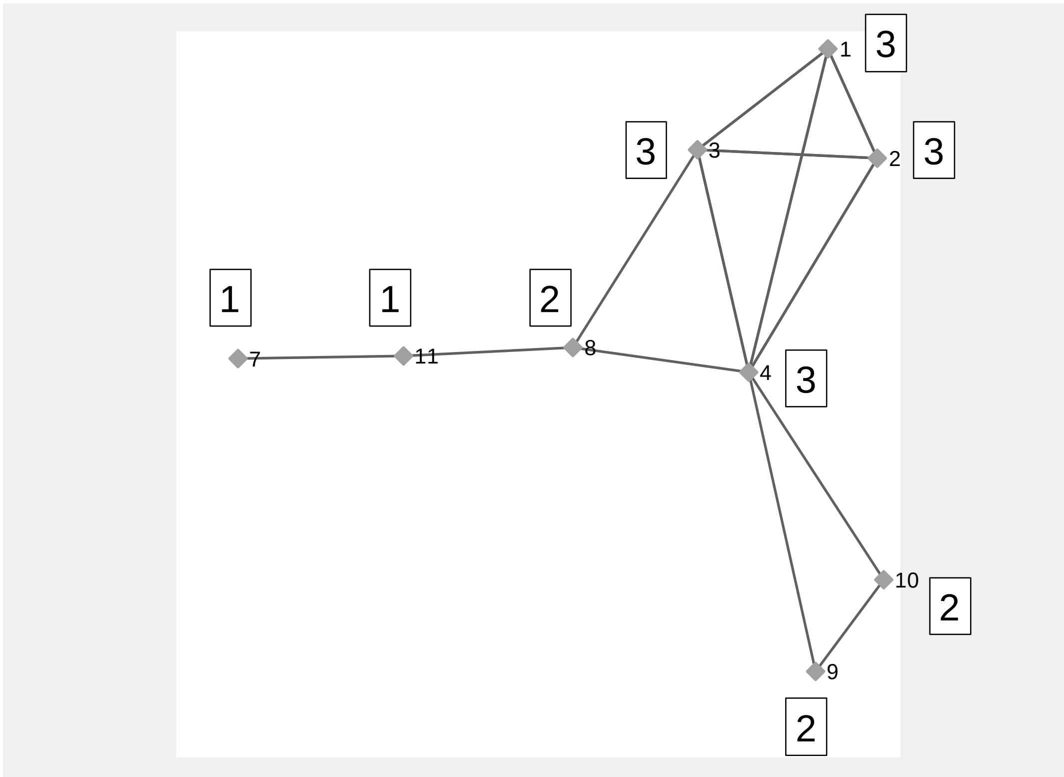

Figure 13: Example of K-core Decomposition (assigned K-core indices in the boxes)

a result, each node is associated with one index of *coreness*, and the network can be viewed as the union of all K-shells, most like the onion is the union of its shells. Every bank is assigned to its shell by its K-shell index. The resulting classification of a node can be very different from the degree, for example for banks at the center of a far-away local banking hub, that may have a relatively high degree, but a very low measure of coreness.

In Figure 14 we have a first look at the simulation results in function of coreness. We start from the simulation results of scenario 3a that are far superior in capturing actual interbank market instability. The first thing to observe is that the Russian interbank network became more complex and layered over time, ranging from a low of only two shells in December 1998 to a high of not less than 12 shells in April 2004. This increasing complexity of the network over time also drives the large difference between scenario 2a and 3a. Indeed, the fact that the interbank liquidity run scenario does so well in capturing the 2004 crisis is related to the increased complexity of the interbank market in 2004 that magnifies the potential impact of liquidity runs on the stability of the system. Also, we clearly observe how individual bank coreness is very strongly related to potential damage to interbank market stability. Higher K-shell indices are firmly related to darker colors (more contagion damage to the system) in every period of our sample, indicating that the failure of banks at the core of the system is essential in the phase transition of the interbank market from liquid to illiquid. In Table 3 we present the estimates of (1). In columns (1) and (4) we introduce all our bank level explanatory variables, with the exception of our index of bank K-coreness. In columns (2) and (5) we repeat this exercise, but only introducing our index of bank K-coreness as explanatory variable. According to all information criteria, the simple regression including only the K-shell index clearly outperforms the other regressions. In columns (3) and (6) we include all variables. The estimates of the K-shell index are very robust, while the point estimate, significance and even signs of the other network variables are heavily affected by the inclusion of the K-shell index. We conclude beyond reasonable doubt that the K-shell index is superior to other network variables in understanding an individual's bank potential contribution to interbank market contagion, confirming the earlier results of Kitsak et al. (2010) in a banking environment.

The size of the bank shows up as a deteminant of the bank level contribution to contagion when we try to explain the individual failing bank's contribution to the share of lost assets (column 4), but that the importance of size falters when we introduce the K-shell index in column 6, forcefully making the point that the coreness of a bank is not necessarily the same as its size.

To ensure these conclusions are robust across time, we re-estimate equation (1) for each time period separately and collect the t-statistics. Figure 15 presents the distribution of those t-statistics for each coefficient. For better visibility all t-statistics above 10 are assigned a value of 10. The results are overwhelmingly clear. In every period considered, the bank's coreness is the best predictor of individual banks' contribution to potential interbank market contagion. Bank coreness is remains highly significant in every time period, and the significance reaches very high levels (t-statistic > 10) in a considerable number of time periods.

We further investigate this point by looking into the weighted K-shell index $K(\alpha)$, which is defined as the K-shell index calculated with only αth percentile of largest links, in our case the $\alpha\%$ largest interbank loans. Our standard K-shell index is then expressed as $K(100)$.When we apply this to our framework and repeat the estimations of the previous paragraph, we find that if we use $K(50)$,thus neglecting the 50th percent smallest contracts, the explanatory power of the regressions diminshes considerably (indicating indeed that interconnectedness matters rather than size) but also that the K-shell index still strongly outperforms any of our other variables in every period, suggesting that our method has potential with even less than complete data and that it may therefore be applicable in reality by the guardians of systemic stability (results available on request). We have also experimented with other more elaborate versions of the weighted K-index, involving the normalisation of the interbank contracts. The results (available on request) were robust though less strong than the results with the unweighted K-shell index, again suggesting that interconnections matter more than size and that even incomplete information on interconnections

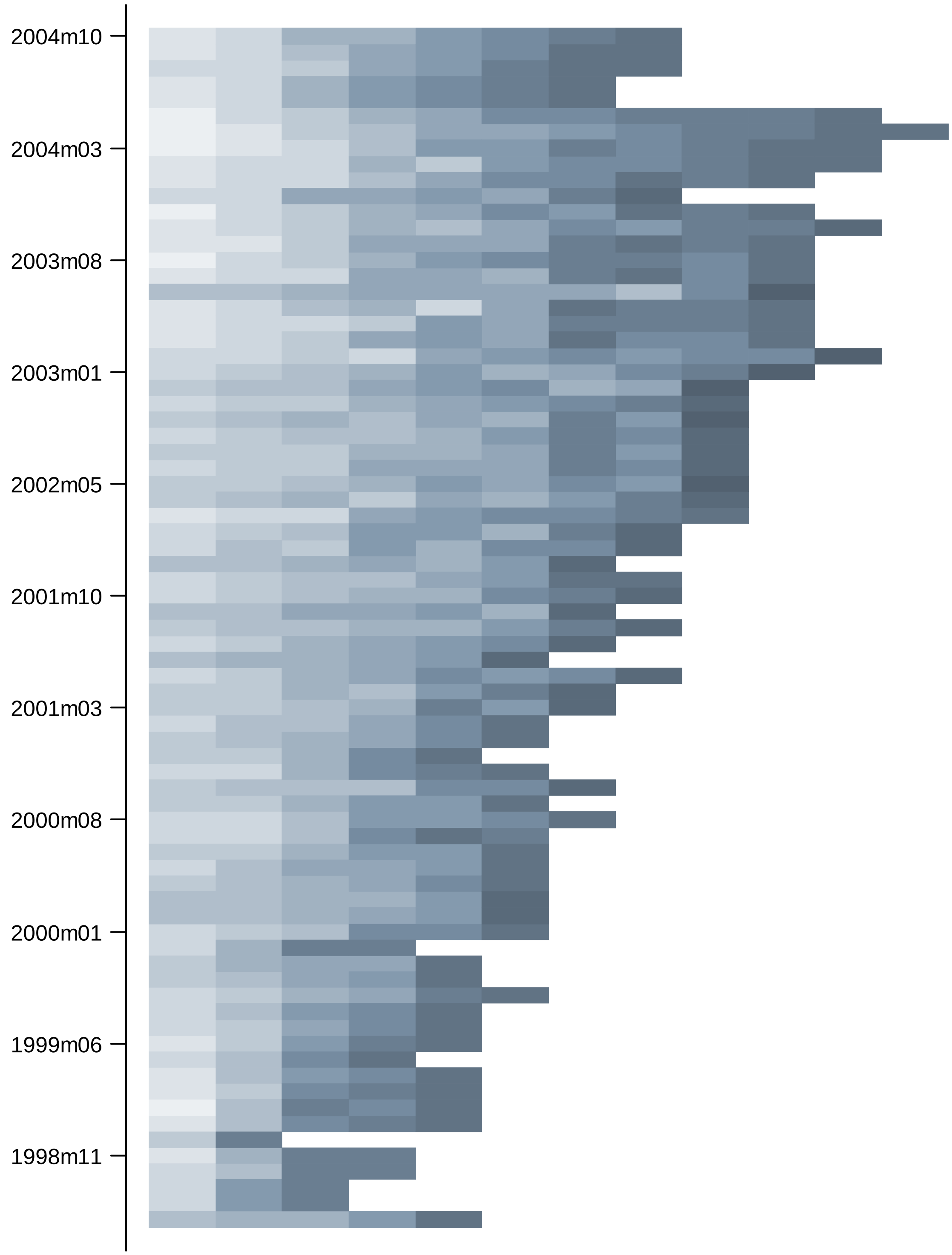

Figure 14: Spreading Capacity & K-cores (% of Failed Assets; Scenario 3a, $\lambda = \rho = \delta = \mu = 100\%$)

Table 3: Identifying Influential Spreaders

	C = Share of failed banks			C = Share of failed assets		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
NI	1.11***		-0.71***	2.88***		-2.00***
	(8.6)		(-5.6)	(7.7)		(-5.4)
NO	2.32***		0.17*	5.55***		-0.22
	(11.2)		(1.9)	(9.9)		(-1.0)
VI	0.38**		0.30***	1.15**		0.93***
	(2.6)		(3.0)	(2.5)		(2.9)
VO	0.09		0.10*	0.33*		0.35
	(1.6)		(1.7)	(1.7)		(1.6)
Betw	-0.74***		0.56***	-1.89***		1.59***
	(-6.9)		(5.4)	(-6.4)		(5.3)
Size	0.04		-0.02	0.11*		-0.04
	(1.5)		(-1.4)	(1.6)		(-0.7)
K-shell index		0.01***	0.01***		0.02***	0.02***
		(47.6)	(33.2)		(42.6)	(32.1)
Constant	-0.04***	-0.05***	-0.05***	-0.11***	-0.14***	-0.14***
	(-21.6)	(-29.4)	(-29.4)	(-20.5)	(-27.7)	(-27.9)
Observations	56,782	56,782	56,782	56,782	56,782	56,782
AIC	-35266	-39023	-40119	3026	-443.9	-1297
BIC	-34532	-38334	-39376	3760	245.0	-554.1
ML (Cox-Snell) R2	0.268	0.315	0.328	0.233	0.278	0.289
McKelvey-Zavoina's R2	0.328	0.397	0.409	0.287	0.355	0.365

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

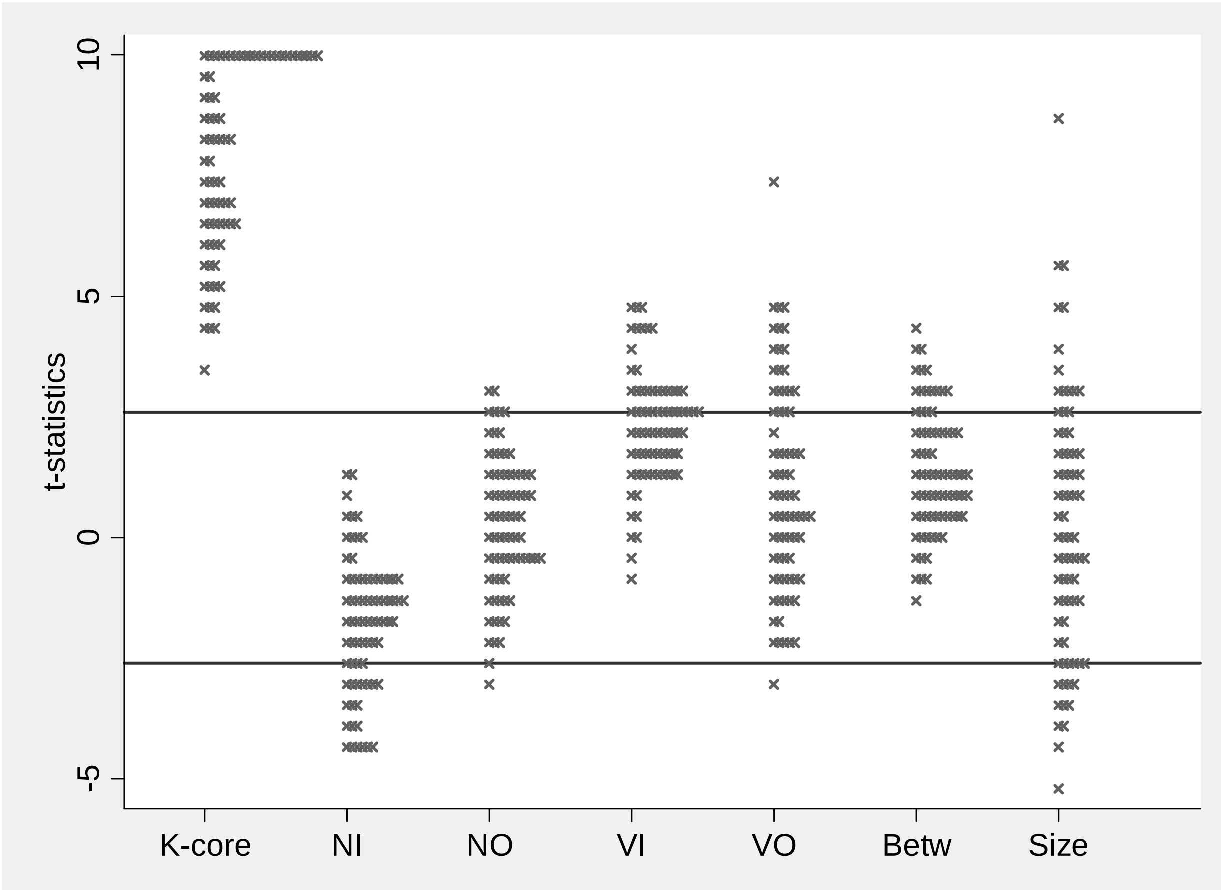

Figure 15: Influential Spreaders over Time: (% of Failed Assets; Scenario 3a, $\lambda = \rho = \delta = \mu =$ 100%)

may be helpful.

It seems clear that if policymakers want to steer clear from crises driven by liquidity runs.they should take into account individual bank coreness in the design of capital rules and in the design of liquidity support in times of crisis. Requiring higher capital from core banks and in exchange providing them ample liquidity in times of crisis seems a wise policy to increase the stability of the interbank market. In judging a bank's coreness, it seems advisable that bank policy makers should take into account the tieredness and complexity of the banking system, rather than just bank size The K-shell index seems to be the best measure currently available to make this judgment. Less than complete data on interconnections may suffice to draw the right conclusions, making the K-shell index a realistic tool for the guardians of systemic stability.

7 Conclusion

We provide a new way of simulating the impact of interbank market contagion on the stability of the interbank market. We not only look at credit losses and capital, but also turn attention to funding liquidity losses, fire sales of assets and active liquidity runs on infected banks that change the network topology during a crisis. Employing a Russian dataset of time-varying bilateral interbank exposures with contract data, and monthly balances and profit and loss accounts, we show that this combination of contagion channels is essential to understand two very different real life interbank market panics. Especially allowing active liquidity runs on infected banks turns out to be essential to properly capturing reality. We then proceed by trying to predict individual banks' contribution to the simulated contagion, relying only on the bank's position in the network. We find that there is one and only one robust and reliable predictor of a bank's potential to spread contagion, namely its coreness to the banking system as measured by the K-shell index. We therefore claim to have found a simple and robust way to identify those banks that now commonly referred to as Too-InterConnected-To-Fail, even in fairly big and complex networks.

It seems clear that policymakers should take this information into account in their design of capital rules and in the design of liquidity support in times of crisis. Requiring higher capital from core banks and in exchange providing them ample liquidity in times of crisis seems to have the benefit of increasing the stability of the interbank market. This requires that the supervisors have information on the topology of the network. Further theoretical and empirical research is needed to study possible trade-offs.

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9 Appendices

9.1 Data on Interbank Exposures

The sample period is 1998m7 - 2004m10. The data on bilateral interbank exposures comes from reports "On Interbank Loans and Deposits" (official form's code 0409501), a part of standard disclosure requirements supplied to the regulator on a monthly basis. Each record in the database identifies the lender, the borrower, the contract type (see Table 4 for an overview), the time period, the beginning and the end of period balances, the debit and credit turnovers, the interest rate and the maturity date. After dropping transactions with missing entries we are left with about 3,7 mln records.

Table 4: Types of Interbank Market Contracts

	Interbank Liabilities				Interbank Assets			
	Loans from		Deposits of		Loans to		Deposits with	
Maturity	home	foreign	home	foreign	home	foreign	home	foreign
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
overdraft	31301	31401			32001	32101		
< 1 day	31302	31402	31502	31602	32002	32102	32202	32302
2-7 d	31303	31403	31503	31603	32003	32103	32203	32303
8-30 d	31304	31404	31504	31604	32004	32104	32204	32304
31-90 d	31305	31405	31505	31605	32005	32105	32205	32305
91-180 d	31306	31406	31506	31606	32006	32106	32206	32306
0,5-1 y	31307	31407	31507	31607	32007	32107	32207	32307
1-3 y	31308	31408	31508	31608	32008	32108	32208	32308
> 3 y	31309	31409	31509	31609	32009	32109	32209	32309
demand	31310	31410	31501	31601	32010	32110	32201	32301
bankcards			31510	31610			32210	32310
overdue	31702	31703	31702	31703	32401	32402	32401	32402

Note: The table reports account numbers from the bank chart of accounts corresponding to contract types of different maturity and counterparty's origin. A loan is a contract initiated by the borrower, while a deposit is initiated by the lender.

Each transaction between two *domestic* banks should, in principle, be recorded twice in the database: on the asset side of the lender and the liability side of the borrower. This pattern does not always hold:

1. some claims recorded by lenders can not be traced in the borrowers' data and vice versa
2. often records made by two counterparties seem to refer to the same transaction but differ in one or two details: the specified account number, interest rate, maturity date etc.

We do not see a safe way to combine lenders' and borrowers' data into one comprehensive dataset without the risk of counting some transactions twice. Instead we opt to rely on lenders' data in what follows, but redo all the analyses using borrowers' data as a robustness check.[8] None of our conclusions are sensitive to this choice.

The two most frequently encountered contract types accounting for more than 60% of all database records are accounts 32002 and 32003 - loans between domestic banks for up to a week (see Table 4). Most of those loans, however, are of little interest to us, as they are both granted and repayed within one month leaving a zero end-of-period exposure. For this paper instead we focus on transactions with a non-zero end-of-period balance. That leaves us with about 370,000 records, which are somewhat more equally distributed across the different contract types (see Figure 16).

[8] Transactions involving a foreign counterparty are always recorded *once* in the database - by the domestic bank. For those transactions we always use *all* the available data.

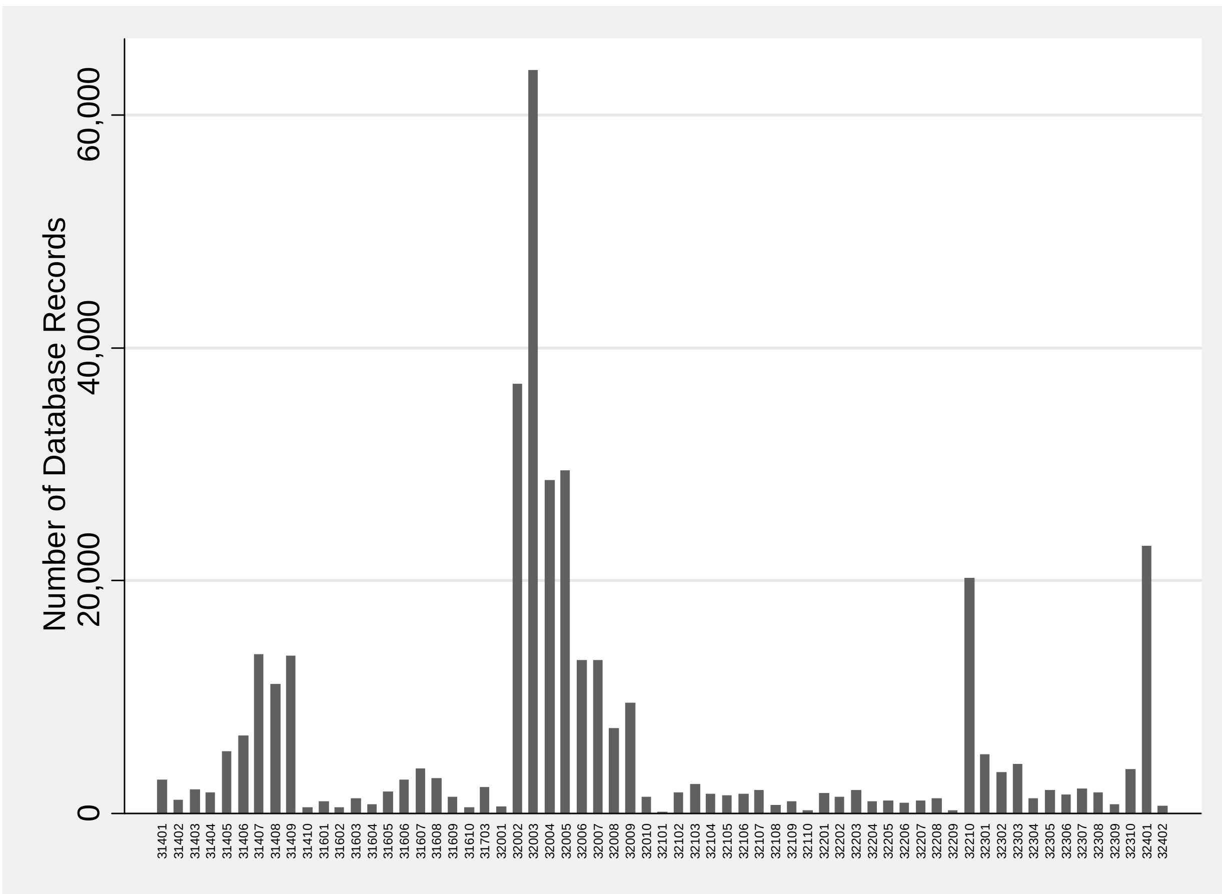

Figure 16: Distribution of Interbank Transactions by Contract Type