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## Systemic Risk: A More Rigorous and Realistic Simulation

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## **Systemic Risk: A More Rigorous and Realistic Simulation**

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## **Introduction**

The occurrence of any financial setback or disaster generates fears, which are promptly reflected in the bond and stock markets, and invariably invites discussions on the stability of the international financial system. As a consequence, financial institutions undergo, and wisely so, extensive reviews of their risk management models, and regulators grab the headlines with suggestions of ways (new regulation) to "stabilize" the financial system in order to prevent systemic failure. Consequently, the dominant question is: Can financial systems fail, or is a liquidity crisis the worst that can occur from a financial crisis?

The series of problems documented in Exhibit I fuel the discussion on a rather regular basis. Add to these, company specific risk management setbacks, the relevant global crises in Asia, Russia and in Latin America, and the fear factor becomes even more exploitable.

### **Some Recent Trade Losses:**

	<b>Loss</b>	<b>Trading activity</b>	
	<b>(\$ million)</b>		
<b>Kidder Peabody</b>	<b>1994</b>	<b>350</b>	<b>Bond Trading</b>
<b>Askin Capital Management</b>	<b>1994</b>	<b>600</b>	<b>Mortgage-based securities</b>
<b>Barings</b>	<b>1995</b>	<b>1400</b>	<b>Derivatives</b>
<b>Daiwa Bank</b>	<b>1995</b>	<b>1100</b>	<b>Bond trading</b>
<b>Salomon</b>	<b>1995</b>	<b>280</b>	<b>Accounting errors</b>
<b>Sumitomo</b>	<b>1996</b>	<b>1800</b>	<b>Unauthorized commodity trade</b>
<b>MGAM</b>	<b>1996</b>	<b>710</b>	<b>Unauthorized investments</b>
<b>NatWest</b>	<b>1997</b>	<b>112</b>	<b>Interest rate options</b>
<b>Bank of Tokyo-Mitsubishi</b>	<b>1997</b>	<b>83</b>	<b>Errors in derivatives model</b>
<b>Salomon</b>	<b>1997</b>	<b>100</b>	<b>Share trading</b>
<b>Chase Manhattan</b>	<b>1997</b>	<b>160</b>	<b>Bond trading</b>
<b>Union Bank of Switzerland</b>	<b>1997</b>	<b>700</b>	<b>Poor derivatives</b>
<b>Salomon Smith Barney</b>	<b>1998</b>	<b>300</b>	<b>Fixed income/global arbitrage</b>
<b>Bank America</b>	<b>1998</b>	<b>529</b>	<b>Trading loss</b>

This paper deals with the issue of systemic failure. It demonstrates that systemic failure is practically impossible under the least restrictive assumptions of bank management behavior and the prudent man rule.

The number of variables involved in our model was too large to allow for a closed form solution for the estimation of the probability of a systemic failure. Consequently, we opted for a simulation using some of the elements of a model developed by McAndrews and Wasilyew. Our simulation allows the largest bank in a local economy to fail, for different size banks, for different recovery rates on loans in the event of failure, for distribution of loans across existing banks, and for different numbers of banks in the system.

Our first attempts to reproduce the results of McAndrews and Wasilyew were not successful without changing the value for the key parameter: variance of net debit. Their results, that systemic risk increases with the size of the banking industry, the likelihood of interbank loans and the possible size of bank payments, are due to a model that allows banks to borrow money far in excess of their asset size. Our proposed model is more flexible and more ambitious. Our results show that each of our modifications reduces the probability of systemic risk. These results contrast with the results of the original model. Our results suggest that a heavily integrated banking system with only a few regulations possess minimal, if any, systemic risk.

This paper is organized as follows: section 1 delivers the foundation to the model; section 2 describes the basic model; section 3 presents the results of the basic model; section 4 describes

the modifications to the model; section 5 presents the results of our simulations; and section 6 summarizes the results of the research.

### **Model Foundation**

Systemic risk, the possibility that the sudden unanticipated failure of one or several banks could trigger a "domino-like" collapse of a large segment of the banking system, has been the subject of a number of recent publications. See: Aglietta (1996), Angelini, Maresca and Russo (1994), Bordo, Mizrach and Schwartz (1995), Giles (1996), and Kaufman (1994). Government has responded by establishing itself as a lender of last resort, establishing the deposit insurance system, and instituting a large set of regulations aimed at minimizing the danger of a systemic failure. As banks increasingly engaged in interbank loans, the foreign exchange markets, OTC derivative trading, and increasingly count on worldwide settlement systems, the concerns about systemic risk have grown.

Several studies on systemic risk have focused on the interbank loan market and the settlement systems. On an average day, many trillions of dollars pass through the world's payment networks and settlement systems. Daylight overdrafts are often huge, exceeding the capital basis of the bank. The two largest payment systems, Fedwire and CHIPS, have received the most attention. Most authors have focused on possible ripple effects in CHIPS, since the Federal Reserve guarantees payment finality in the Fedwire system that it administers. In his 1986 study, Humphrey (1986) took actual CHIPS balance sheets, and simulated the effect of one bank, usually the largest debtor on a given day, defaulting. His results were disturbing, demonstrating that the unwinding linkage used by CHIPS could indeed lead to a large number of linked failures.

Due to these findings, CHIPS instituted new reserve requirements and regulations aimed at reducing these risks, but the study of McAndrews and Wasilyew (1995), henceforth referred to as MW, still finds unsettling possibilities. The bank settlement system is not the only area of concern. The foreign exchange market could be a source of systemic risk; the ghost of the Herstatt Bank failure is still very much alive. Derivatives are probably less of a concern, since the netting arrangements tend to keep the settlement payments small, and since members post large collateral and are limited in the amount of overdraft they can incur.

In this paper, we have chosen to begin with the reexamination of the simulation outlined in MW's paper: "Simulations of Failure in a Payment System" (1995). The paper's value lies in the framework it provides for analyzing systemic risk. While there are considerable doubts about the validity of their model, and especially its application and results, MW did provide some roadmaps for investigating three issues: 1) how does the number of banks in a system affect the possibility of systemic risk? 2) How does the likelihood of any two banks in the system exchanging loans (payments) affect the possibility of systemic risk? 3) How does the size of payments between banks affect the possibility of systemic risk? We see these three properties as key elements of the banking system: number of banks, probability of interbank loans, and size of loans. The MW results suggest that the probability of extreme failure in the payment system increases with the number of participants, the likelihood that any two banks exchange payments and with the size of payments between banks. While we agree with their conclusions based upon their model, we do not agree with the structure of their model. We will show that their model is too simplistic to produce realistic scenarios, and that by applying a simple rule within the payment system; the probability of systemic risk vanishes.

### **Description of the basic model:**

In the basic model, which is based upon the MW simulation, the banking system consists of equal sized banks loaning money to each other. The banking system is a closed system; hence, the sum of all debt within the system is equal to the net credit within the system. Simulation begins by creating loans between banks, closing the bank with the largest net debt, and eliminating all of the payments to and from the defaulting bank. This forces banks that have loaned money to the defaulting bank to either absorb the loss or close. The condition used to determine if a bank must close is the condition of the *unexpected* net loss. The term unexpected net loss was first used by David Humphrey (1986) who was also the first to simulate the effects of a failure in the payment system. Banks that experience unexpected net losses beyond a pre-established threshold are forced to close and their payments are eliminated as well. The process continues until a subset of banks, if any, are able to successfully settle the payments amongst themselves. MW focused on three measures of successful settlement of payments: (1) the probability that the unwinding finds a non-zero subset of banks which can support the payments, (2) the fraction of surviving banks and (3) the fraction of the payments remaining after the default of the largest net debtor and the subsequent unwinding. These measures are in fact, acceptable indicators of the probability of systemic risk in the banking system.

The key parameters in the model are:  $N$ , the number of banks;  $p$ , the probability of any two banks exchanging payments (henceforth known as interaction probability);  $d$ , the threshold level of unexpected net debit (henceforth known as payment default threshold); and  $\sigma^2$ , the variance of the bilateral net debit between any two banks. This last parameter is critical as it affects the size

of possible payments between any two banks. MW used values of 5 to 100 for the number of banks, and values of 0.5, 0.7 and 0.9 of the interaction probability. Since all banks possess an asset size of one, they used values of 0.2 and 0.3 for the payment default threshold, and values of 0.2 and 0.4 of the variance of bilateral net debit.

In the simulation, once the key parameters are set, the simulation begins by assigning, at random, connection between banks, i.e., the simulation begins by drawing payment partners. The interaction probability parameter,  $p$ , is used to set the probability that there is an exchange between any two banks. This is done by creating a binomial distribution where  $p$  is the mean for the distribution. In the MW simulations, the value 50%, 70% and 90% were used as the probability that any two banks exchange payments. The simulation continues by completing the matrix of connections between banks. For every connection, the simulation then chooses at random a bilateral net payment,  $B_{ij} = Z_{ij} - Z_{ji}$ , where  $Z_{ij}$ , is that amount bank  $i$  owes bank  $j$ . For pairs of banks that are not exchanging payments, the bilateral net debit is set to zero.

To create the random values for the bilateral net debit, the simulation uses a normal or Gaussian distribution centered on zero with the variance for this distribution,  $\sigma^2$ , being the variance of bilateral net debit - key and present parameter for the simulation. Since the distribution is centered on zero, the mean value for the bilateral net payments is zero. This means that there is an equal chance that bank  $i$  or bank  $j$  is loaning the money. More importantly is the value chosen for the variance of net debit. As the variance increase, the probability that one bank owes a significant amount of money to another also increases. The simulation then calculates the multilateral net debit for each bank:



$$F_i = \sum B_{ij}.$$

The initial value for each bank is stored as  $F_i(0)$  so that it can be used for comparison with future multilateral net debit values.

The simulation continues by identifying the bank with the largest net debit. This bank is closed and is dropped from the run. All payments to and from this bank are also dropped. The multilateral net debit for the remaining banks is then recalculated. The multilateral net debit for any bank that has a connection with the failed bank will change. For each bank, the new value for the multilateral net debit,  $F_i$ , is then compared with the original multilateral net debit value,  $F_i(0)$ . The difference,  $F_i - F_i(0)$ , is defined as the unexpected net debit. If the difference between the two values exceeds the payment default threshold, i.e., the unexpected net debit threshold level, the bank is considered to be in financial trouble, is then closed and dropped from the run. All payments to and from this bank are removed. The simulation continues by recalculating the multilateral net debit for each of the remaining banks. Again, for each bank, the new value is compared to the original multilateral net debit value and should any remaining bank suffer an unexpected net debit beyond the threshold, it too, is dropped from the run. The process continues until none, if any, of the remaining banks possess an unexpected net debit beyond the threshold.

As an example, consider a simulation that consists of two banks where  $d$ , the payment default threshold, is 0.2. Assume bank A is assigned a payment of 0.4 to bank B, then the initial value for the  $F_A(0)$  (for bank A) is +0.4 and the initial value for  $F_B(0)$  (for bank B) is -0.4. Since bank A possesses the largest net debit, it is closed and all of its payments are eliminated. The new

value for  $F_B$  for bank B is now 0. The difference between the new value and the original value,  $F_B - F_B(0)$ , is +0.4. Since this is greater than the payment default threshold, bank B closes as well. When the run ends the relevant data is saved. Important data include the percentage of banks and the percentage of payments remaining after the initial net debtor and its payments have been dropped. For example, consider a simulation where there are four banks and five payments. Once the top defaulter and associated payments are eliminated, there are three banks and three payments. If, after all the interactions, there are only two banks remaining and one payment, the fraction of remaining banks is  $1/4$  while the fraction of remaining payments is  $1/5$ . The simulation is executed 500 times with the same initial conditions and the averages for the results are recorded.

### **Results from the basic model:**

The results of the simulation show the mean percentage of payments and banks remaining after the largest net debtor and its payments were eliminated for different values of the variances of net debit, payment default threshold, number of banks and probability of interaction. The data suggests the following: the success of finding a subset of banks that can successfully settle the payments amongst themselves after unwinding does depend upon the four key parameters: 1) the number of banks, 2) the probability of an interaction between any two banks, 3) the payment default threshold, and 4) the size of possible payments. What is remarkable, however, is that the MW data points to an increase in unsettled payments when the likelihood of interactions increases, when more banks participate and when the size of payments between banks increase. For example, MW report that for a banking system where the variance of bilateral net debit is 0.4, the payment default threshold is 0.3 and the probability of interaction was 0.7, the fraction of

payments that survive decreases from 0.59 to 0.18 when the number of banks increases from 5 to 25. If the probability of interaction increases from 0.7 to 0.9, the fraction of surviving payments falls from 0.51 (with 0.35 error) to 0.16 (with 0.09 error) for banking systems of  $N=5$  and 25 respectively.

After some experimentation we were able to reproduce nearly all of MW results, within statistical error, by reducing the variance of bilateral net debit, i.e., the possible size of payments between any two banks. If we use their reported value for the variance, under the best of conditions, the percentage of banks and the percentage of payments that survive the unwinding after the largest net debtor was removed is exceedingly small (less than 10 percent). (See Table Set I for a listing of results using identical values reported by MW for the key parameters.) Not surprisingly, the model suggests that payments of smaller size reduce the risk of payment failure. However their model promotes failure within the system under unrealistic scenarios, and contains some unrealistic consequences regarding failed institutions. In the following section, we identify some problems with the basic model and present a modified model that addresses these problems.

### **Description of model modifications – The more realistic model:**

We concentrated on two issues: 1) why does failure increase with  $N$ , the number of banks, and 2) why does the failure rate increase with  $p$ , the interaction probability. Interestingly, MW identifies the reason for these two results. If one increases the number of potential payments by a single bank by either increasing the number of banks in the pool and/or the probability of an interaction between any two banks, one increases the variance of an individual bank's multilateral

net debit,  $F_i$ . It can be shown that the variance for the multilateral net debit is  $(k-1)\sigma^2$  where  $k$  is the number of banks with which a bank exchanges payments. Since the variance for the multilateral net debit can be increased, not surprisingly, one can produce banks with very large net debt, well beyond the assets of the bank. Once an extremely debt ridden bank is removed from a system, it carries with it all the other banks which have loaned it money.

Once we had determined the causes for the results from the basic model, we proceeded to make the following modifications and evaluated their effects:

- We altered payments so that loans to a failed bank were settled at some percentage of the original value and that loans from a failed bank were still considered due in full. We created a new parameter to describe the loan sale rate. Loans to a defaulting bank were settled at the loan sale rate.

- We altered the variance of net debit to include the effect of increased payment options for a bank by dividing the variance by the interaction probability and the number of banks.

- We included the fact that a system will have a distribution of bank sizes. For simplicity, we created two types of banks, small and large and established two new parameters, one to describe the size of a large bank in relation to a small bank, and the other to describe the percentage of large banks to small ones. The actual percentage within a single run was determined by a random binomial distribution with the mean equaling the large-to-small ratio.

We made these modifications to better reflect the actual events that occur when a bank is closed. For example, when a bank fails, loans from that bank are still expected to be honored, and hence another bank, which owes money to a failed bank, should not assume that its debt is canceled. In

addition, loans from the failed banks are often sold on the market at a discounted rate that means that the banks that possess the loan are not simply left with zero income, but a small percentage of the original loan.

Changing the variance of the net debit by distributing loans throughout the system reduces the unrealistic characteristic of the basic model where a single bank could owe other banks an amount far in excess of its assets. As a result, loans are more freely and intelligently distributed through out the system.

In the basic model, all banks were of identical size. In the US, a small portion of the banks is significantly larger than the majority of banks. We wish to determine if the distribution of size increases or decreases the chance of systemic risk. We also wish to determine whether the size of large banks compared to small banks increases the chance for failure of small banks should a large bank fail. Loans between banks of identical sizes would be unchanged; however, loans between banks of different sizes would have to be adjusted by the bank's size. In our simulation, if a loan was to be established between banks of different sizes, the program calculates the bank loan based on the smaller bank's size and then assigns to the larger bank the amount divided by the larger bank's size. We chose this policy so that a large loan from a large bank could never be assigned to a smaller bank.

With each modification, we executed the simulation with no modification and with a single modification and then compared the results. This helped us determine how these new parameters

might affect the system. We also executed the simulation with multiple modifications and reported the results.

### **Results - basic and modified model:**

The results of our simulation are reported in the tables, which are laid out as follows: unless otherwise noted, for each table, two of the important parameters are held constant and we vary the other two parameters. The two held constant are  $\sigma^2$ , the variance of bilateral net debit and  $d$ , the payment default threshold. Each column corresponds to a specific value for  $N$ , the number of banks, while each row corresponds to a specific value for  $p$ , the probability of interaction (or payment exchange) between two banks. For each element in the tables, two pieces of information are shown: (A) the percentage of payments and (B) the percentage of banks that survive after the top debtor is removed along with its payments and the subsequent unwinding. (These numbers are reported A/B.) As described above, we calculate these two values by first determining the number of payments and the number of banks left after having removed the top debtor and all its payments. We then let the unwinding process occur and recount the number of surviving payments and surviving banks. We store the second set of values as a percentage of the first, repeat this process for the 500 runs and then report the averages of these two percentages.

For example, according to the first table in Table Set 1, for 25 banks at an interaction probability of 0.5, on average, 9 percent of the payments survive and 31 percent of the banks survive.

The first set of tables (Table Set 1) shows the results we obtain when we attempt to reproduce the results of McAndrews and Wasilyew. We used the identical values for the parameters reported

in their paper. While we reproduce only two of their four tables (table A and table B), it is clear we are unable to reproduce their results. For nearly every probability of interaction and number of banks, the percentage of payments that survive is lower than they report. For example, for  $N=25$  and  $p=0.9$ , they report a fraction of surviving payments of 0.20 (or 20 percent). Our results show a survival rate of 6 percent. We wondered why so few payments (and banks) survived given the parameters of the simulation. When we looked at the average debt of the top debtor, we found that as one increases the number of banks and the probability of interaction, the top debtor can have a debt that is many times larger than their asset size. For example, in Table C in Table Set I, for 75 banks where the probability of interaction is 0.9 and the variance of net debit is 0.4, we find that on average, the top debtor has a debt 9 times its size, which is a value we consider highly unlikely. As stated above, this massive debt is a result of an increase in the variance of multilateral net debit. While each loan may be of medium size, as one increases the number of banks, the model allows banks to continue to create new loans with new banks without hindrance. We do not believe this is an accurate reflection of how the banking system works.

In Table Set II, tables A and B, we are able to reproduce the data of McAndrews & Wasilyew. We accomplish this task by dividing the variance of bilateral net debit they report by 10. We are able to reproduce nearly every result to within statistical error. The reduction in the variance of bilateral net debit causes the average size of payments between banks to shrink as well. Not surprisingly, fewer banks have extremely large loans to and from failing banks and hence more banks and more payments survive. However this probability of systemic risk increases with the number of payments. In table C of Table Set II, we report the average debt of the largest debtor.

Not surprisingly, as compared to table C of Table Set 1, by decreasing the probability for very large payments, the average debt of the largest debtor also decreases. For example, for 75 banks where the probability of interaction is 0.9, when the variance of net debit is 0.04 as opposed to 0.4, the mean debt of the largest debtor is 2.78 as opposed to 9. Still, we find that with this model, as the number of banks increases, the mean debt of the largest net debtor also increases hence we are not surprised that when using this model, systemic risk increases with the number of banks.

In Table Set III, we report data on the original model after we made two modifications. These modifications were: 1) loans from a defaulting bank are sold at a discount and 2) loans to a defaulting bank must continue to be paid in full. Table A in Table Set III is identical to table A in Table Set II, except for these two modifications. The loan sale rate is set at 80%, which means that the banks that have loans to a defaulting bank will receive 80% of their net loan. Not surprisingly, this value leads to nearly 100% survival for up to 300 banks. This means that the top net debtor in each run is able to pay off its debtors a sufficient amount so that the other banks do not fail. In table B in Table Set III, we decrease the loan sale rate to 60%. We find some banks begin to fail as we increase the probability of interaction and also increase the number of banks. Table C is identical to table B, except the variance of net debit is increased from 0.02 to 0.04. This makes table C in Table Set III comparable to table B in Table Set II. The loan sale rate in table C is 60%. In this table we begin to see a sudden increase in systemic risk. This is a result of forcing banks that have loans to failed banks to continue to pay off those loans. For a system involving a large number of banks (say 100 or more) with a large probability of interaction, the smaller payment against loans from failed banks is not sufficient enough to



overcome the expectation of paying off loans to other failed banks. This effect becomes even more pronounced when we examine table D. This table is identical to table C, except the payment default threshold is reduced to 0.1. The entangled web of payments traps nearly all banks, as return on bad loans is not sufficient enough to assist a bank in paying loans to other defaulted banks. For example, in table D of Table Set III, for 100 banks where the probability of interaction is 0.5, virtually none of the banks and none of the payments survived after the top debtor was removed from the system. Because we feel our modifications produce a more realistic model of the banking system, Table Set III suggests that systemic risk may be quite real given sufficiently large payments between banks. One could argue that because some payments from a defaulting bank may not appear at the loaning bank's offices for several months, the loan sale rate should actually be 0%. This would produce even more catastrophic results.

### **The diversification rule**

In generating Table Set IV, we attempted to evaluate a technique for reducing the probability of systemic risk that we call the diversification rule. The diversification rule attempts to distribute net debit from a single bank across the entire banking system. Our implementation of the diversification rule was to take the variance of net debit, i.e., the possible size of a loan, and divide by both the probability of interaction and the number of banks. This produces loans between banks that are much smaller and yet, as shown in table C of Table Set IV, banks can still possess large loans. For example, in table C, for 100 banks where the probability of interaction is 0.9, the mean debt of the top defaulting bank was still more than 1.5 times its size in capital which is still an extremely large number.

Table A in Table Set IV is identical to table A in Table Set II except we have added this diversification rule. As one can see, with more banks we decrease the chance of failure by other banks; the system becomes more stable as we add banks. If we increase the variance of net debit to 0.4 which is similar to table B in table Set I, instead of an increase in systemic risk, as we increase the number of banks, the probability of systemic risk decreases. Table C shows that there may be banks with extremely large net debit, however since their payments are spread over the entire banking system, the likelihood of the top defaulting bank causing a total failure within the banking system is extremely small.

To generate table D in Table Set IV, we added the modifications that all loans to a defaulting bank must still be paid and that loans from a defaulting bank are paid back at a reduced amount. With a small set of banks owing large amounts to only a few other banks, there is still a chance that the top defaulting bank can cause the failure of other banks. However, again as we increase the network of loans, the inertia of the system supports the rest of the banks in the event of a failed bank.

Another modification is shown in Table Set V. In the original model, all banks are of identical size. In our next modification, we created two sets of banks; ones that are large and the rest that are small. The large banks make up a small percentage of the total number of banks. Here we attempted determine if the spectrum of bank size contributes to the likelihood of systemic risk. In table A of Table Set V, we used the same parameters and model as used to generate table B of Table Set II. The payment default threshold is 0.2, the variance of net debit is 0.04 and all unpaid loans are eliminated. For all runs in this table, the probability of interaction is set at 0.5,

however the number of banks varies. The mean percentage of banks that are large is set at 10%. The scenario is comparable to the scenario that created the results in the second line of Table B in Table Set II. In table A of Table Set V, we report the survival percentages when the large banks are 10 times larger and then 20 times larger. When compared to Table B in Table Set II, the results show large banks provide added stability to the system, however, there is a limit to the effect of the large banks. There is no difference between banks 10 times and banks 20 times larger than average. Nor did the results change if we increase the mean bank size to 50 times larger. In table B we increase the variance of bilateral net debit to 0.2 which is identical to table A of Table Set I. Again, the interaction probability is 0.5 and again we see minimal affect of bank size on the probability of systemic risk. Only when we examined the system for a very large number of banks, did we note any effect of bank size on the system. At some point, the extremely large banks discontinue providing stability to the system. In table C, we increased the percentage of large banks from 10% to 20% and repeated the experiment. We note that as large banks began to contribute a larger percentage of the payments in the system, the likelihood of total failure of banks increases. In table D and E we repeated the process using the same parameters as in B and C respectively, except, we added our more realistic modification that payments to defaulting banks must still be paid and that payments from a defaulting bank are still made but at a reduced percentage. Tables D and E show that having large banks again provides stability to the system, but does not guarantee it.

Finally, in table F, we apply our diversification rule and see that even with very large banks making very large loans to each other, as long as the loans are spread out throughout the system, the chance of systemic risk is nearly zero.

### **Summary:**

In conclusion, we were able to reproduce the results of McAndrews and Wasilyew once we reduced the variance of net debit, and we expanded the simulation results considerably. By adding banks of variable size and not eliminating payments to failed institutions, we were able to produce a more realistic model for the banking system. More importantly, by applying the simple diversification rule, we found that there is nearly zero chance of systemic risk even if some banks within the system are in extreme debt. This last result may have important implications for the policies of central banks and on regulation of the banking system.

The evidence is rather conclusive that a heavy regulatory burden on the banking sector is not necessary to assure bank stability. What are needed, it appears, are only the prudent man rule, good supervision, and adherence to extensive risk diversification to anchor the stability of the banking system.

## Table Set I: Basic model:

**Table A**

Table entries: average percentage of payments completed in payment system / average percentage of banks remaining after the default of the largest net debtor and the subsequent unwinding of process. Here payment default threshold = 0.2, variance of bilateral net debit = 0.2

Probability of interaction	Number of banks						
	<b>5</b>	<b>25</b>	<b>50</b>	<b>75</b>	<b>100</b>	<b>200</b>	<b>300</b>
<b>0.1</b>	48/70	60/77	32/56	18/42	14/38	11/32	9/30
<b>0.5</b>	23/47	9/31	8/28	7/27	7/26	7/26	7/26
<b>0.7</b>	11/33	7/27	7/26	6/26	6/25	6/25	6/25
<b>0.9</b>	7/26	6/25	6/24	6/24	6/24	6/24	5/23

**Table B**

Table entries: average percentage of payments completed in payment system / average percentage of banks remaining after the default of the largest net debtor and the subsequent unwinding of process. Here: payment default threshold = 0.2, variance of bilateral net debit = 0.4

Probability of interaction	Number of banks						
	<b>5</b>	<b>25</b>	<b>50</b>	<b>75</b>	<b>100</b>	<b>200</b>	<b>300</b>
<b>0.1</b>	38/66	56/73	24/48	15/39	12/35	9/30	8/28
<b>0.5</b>	22/45	8/28	7/27	7/27	6/25	6/25	6/24
<b>0.7</b>	9/30	6/24	6/24	6/24	6/24	6/24	6/24
<b>0.9</b>	9/23	5/22	5/22	5/22	5/22	5/22	5/22

**Table C**

Table entries: average value for bilateral net debit of top defaulting bank across 500 runs. payment default threshold = 0.2, variance of bilateral net debit = 0.4

Probability of interaction	Number of banks						
	<b>5</b>	<b>25</b>	<b>50</b>	<b>75</b>	<b>100</b>	<b>200</b>	<b>300</b>
<b>0.1</b>	0.53	1.48	2.36	3.02	3.68	5.59	7.17
<b>0.5</b>	0.82	3.2	5.1	6.7	8.0	12.4	15.7
<b>0.7</b>	0.96	3.7	6.0	7.9	9.4	14.7	18.6
<b>0.9</b>	1.05	4.1	6.8	9.0	10.6	16.3	21.19

## Table Set II: Basic Model with corrections

**Table A**

Table entries: average percentage of payments completed in payment system / average percentage of banks remaining after the default of the largest net debtor and the subsequent unwinding of process. Here: payment default threshold = 0.2, variance of bilateral net debit = 0.02

Probability of interaction	Number of banks						
	<b>5</b>	<b>25</b>	<b>50</b>	<b>75</b>	<b>100</b>	<b>200</b>	<b>300</b>
<b>0.1</b>	81/91	89/95	88/93	84/91	77/87	27/51	19/44
<b>0.5</b>	71/84	38/59	19/43	15/38	13/36	11/32	9/30
<b>0.7</b>	67/81	26/50	15/39	12/35	12/34	10/31	9/29
<b>0.9</b>	58/74	19/42	13/36	12/34	11/33	9/29	8/29

**Table B**

Table entries: average percentage of payments completed in payment system / average percentage of banks remaining after the default of the largest net debtor and the subsequent unwinding of process. Here: payment default threshold = 0.2, variance of bilateral net debit = 0.04

Probability of interaction	Number of banks						
	<b>5</b>	<b>25</b>	<b>50</b>	<b>75</b>	<b>100</b>	<b>200</b>	<b>300</b>
<b>0.1</b>	72/85	79/88	72/85	54/72	36/59	18/42	14/37
<b>0.5</b>	52/72	20/44	13/36	12/33	10/32	9/29	8/28
<b>0.7</b>	40/62	14/37	11/33	10/31	9/30	8/28	8/27
<b>0.9</b>	32/54	11/33	9/30	9/30	8/29	8/27	7/27

**Table C**

Average value for bilateral net debit of top defaulting bank across 500 runs.  
payment default threshold = 0.2, variance of bilateral net debit = 0.04

Probability of interaction	Number of banks						
	<b>5</b>	<b>25</b>	<b>50</b>	<b>75</b>	<b>100</b>	<b>200</b>	<b>300</b>
<b>0.1</b>	0.17	0.47	0.74	0.97	1.20	1.78	2.24
<b>0.5</b>	0.25	0.97	1.60	2.10	2.54	3.89	5.00
<b>0.7</b>	0.31	1.15	1.87	2.50	2.96	4.60	5.89
<b>0.9</b>	0.35	1.30	2.11	2.78	3.36	5.24	6.80

### Table Set III: Loans from defaulting bank are sold at discount.

**Table A**

Table entries: average percentage of payments completed in payment system / average percentage of banks remaining after the default of the largest net debtor and the subsequent unwinding of process. Here: payment default threshold = 0.2, variance of bilateral net debit = 0.02, loan sale rate = 80%

Probability of interaction	Number of banks						
	5	25	50	75	100	200	300
0.1	100/100	100/100	100/100	100/100	100/100	100/100	100/100
0.5	100/100	100/100	100/100	100/100	100/100	100/100	100/100
0.9	100/100	100/100	100/100	100/100	100/100	100/100	100/100

**Table B**

payment default threshold = 0.2, variance of bilateral net debit = 0.02, loan sale rate = 60%

Probability of interaction	Number of banks						
	5	25	50	75	100	200	300
0.1	100/100	100/100	100/100	100/100	100/100	100/100	100/100
0.5	100/100	100/100	100/100	100/100	100/100	100/100	95/96
0.9	100/100	100/100	99/98	97/97	97/97	94/94	94/94

**Table C**

payment default threshold = 0.2, variance of bilateral net debit = 0.04, loan sale rate = 60%

Probability of interaction	Number of banks						
	5	25	50	75	100	200	300
0.1	99/99	99/99	99/99	99/99	99/99	99/99	98/99
0.5	99/99	96/96	85/85	67/67	53/53	33/33	15/15
0.9	98/99	80/80	54/54	40/40	31/31	12/12	5/5

**Table D**

payment default threshold = 0.1, variance of bilateral net debit = 0.04, loan sale rate = 60%

Probability of interaction	Number of banks						
	5	25	50	75	100	200	300
0.1	91/88	93/93	90/90	74/74	29/28	0.2/0.2	0/0
0.5	81/80	7/6	0.3/0.3	0/0	0/0	0/0	0/0
0.9	66/61	0.6/0.6	0/0	0/0	0/0	0/0	0/0

## Table Set IV: Diversification rule

**Table A**

Table entries: average percentage of payments completed in payment system / average percentage of banks remaining after the default of the largest net debtor and the subsequent unwinding of process. Here: payment default threshold = 0.2, variance of bilateral net debit = 0.02, all unpaid loans eliminated

Probability of interaction	Number of banks						
	<b>5</b>	<b>25</b>	<b>50</b>	<b>75</b>	<b>100</b>	<b>200</b>	<b>300</b>
<b>0.1</b>	68/84	97/98	100/100	100/100	100/100	100/100	100/100
<b>0.5</b>	94/97	100/100	100/100	100/100	100/100	100/100	100/100
<b>0.9</b>	98/99	100/100	100/100	100/100	100/100	100/100	100/100

**Table B**

payment default threshold = 0.2, variance of bilateral net debit = 0.4, all unpaid loans eliminated

Probability of interaction	Number of banks						
	<b>5</b>	<b>25</b>	<b>50</b>	<b>75</b>	<b>100</b>	<b>200</b>	<b>300</b>
<b>0.1</b>	49/68	63/79	51/70	42/63	35/60	27/52	30/53
<b>0.5</b>	24/47	25/49	26/50	31/53	39/58	91/94	99/99
<b>0.9</b>	14/37	21/45	39/57	64/75	83/89	100/100	100/100

**Table C**

Average value for bilateral net debit of top defaulting bank across 500 runs. payment default threshold = 0.2, variance of bilateral net debit = 0.4

Probability of interaction	Number of banks						
	<b>5</b>	<b>25</b>	<b>50</b>	<b>75</b>	<b>100</b>	<b>200</b>	<b>300</b>
<b>0.1</b>	1.06	1.32	1.48	1.69	1.64	1.78	1.83
<b>0.5</b>	0.73	1.22	1.42	1.49	1.57	1.74	1.81
<b>0.9</b>	0.71	1.23	1.43	1.51	1.55	1.75	1.86

**Table D**

payment default threshold = 0.2, variance of bilateral net debit = 0.4, loan sale rate = 60%

Probability of interaction	Number of banks						
	<b>5</b>	<b>25</b>	<b>50</b>	<b>75</b>	<b>100</b>	<b>200</b>	<b>300</b>
<b>0.1</b>	75/75	92/92	97/97	99/99	99/99	100/100	100/100
<b>0.5</b>	81/78	98/99	99/99	100/100	100/100	100/100	100/100
<b>0.9</b>	96/85	99/99	100/100	100/100	100/100	100/100	100/100



## Table Set V: Variable size banks:

**Table A**

Table entries: average percentage of payments completed in payment system / average percentage of banks remaining after the default of the largest net debtor and the subsequent unwinding of process. Here: payment default threshold = 0.2, variance of bilateral net debit = 0.04, all unpaid loans eliminated, probability of interaction = 0.5, percentage of large banks = 10%

Bank size	Number of banks						
	5	25	50	75	100	200	300
10	56/73	29/51	27/47	21/42	21/41	19/38	16/35
20	57/75	31/53	24/44	20/40	22/41	22/39	17/36

**Table B**

payment default threshold = 0.2, variance of bilateral net debit = 0.2, all unpaid loans eliminated, probability of interaction = 0.5, percentage of large banks = 10%

Bank size	Number of banks						
	5	25	50	75	100	200	300
10	28/53	20/40	18/36	14/33	14/33	7/27	6/25
20	34/55	19/39	17/35	18/36	16/34	16/34	12/30
50	30/54	17/37	19/38	20/38	19/37	19/37	21/37

**Table C**

payment default threshold = 0.2, variance of bilateral net debit = 0.2, all unpaid loans eliminated, probability of interaction = 0.5, percentage of large banks = 20%

Bank size	Number of banks						
	5	25	50	75	100	200	300
10	38/61	31/49	20/39	14/33	10/30	6/26	6/26
20	39/58	25/44	29/46	28/45	26/43	11/20	6/25
50	35/59	28/47	28/46	29/46	29/46	29/46	30/46

**Table D**

payment default threshold = 0.2, variance of bilateral net debit = 0.2, probability of interaction = 0.5, percentage of large banks = 10%, loan sale rate = 60%

Bank size	Number of banks						
	5	25	50	75	100	200	300
10	80/77	17/16	15/15	13/13	13/13	8/8	2/2
20	81/79	15/15	15/15	12/12	13/13	12/12	11/11
50	83/79	16/15	12/12	14/14	12/12	14/14	12/12

**Table E**

payment default threshold = 0.2, variance of bilateral net debit = 0.2, probability of interaction = 0.5, percentage of large banks = 20%, loan sale rate = 60%

Bank size	Number of banks						
	<b>5</b>	<b>25</b>	<b>50</b>	<b>75</b>	<b>100</b>	<b>200</b>	<b>300</b>
<b>10</b>	83/81	36/35	23/23	24/24	18/18	0/0	0/0
<b>20</b>	82/81	32/32	27/27	25/25	29/29	24/24	6/6
<b>50</b>	82/82	31/31	27/27	27/27	30/30	30/30	30/30

**Table F**

payment default threshold = 0.2, variance of bilateral net debit = 0.2, probability of interaction = 0.5, percentage of large banks = 10%, loan sale rate = 60%, with diversification rule

Bank size	Number of banks						
	<b>5</b>	<b>25</b>	<b>50</b>	<b>75</b>	<b>100</b>	<b>200</b>	<b>300</b>
<b>10</b>	95/93	99/99	100/100	100/100	100/100	100/100	100/100
<b>20</b>	94/94	100/100	100/100	100/100	100/100	100/100	100/100
<b>50</b>	92/92	99/99	100/100	100/100	100/100	100/100	100/100

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