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ABSTRACT

Measures of risk of domino effect (contagion) transmitted through interbank market are discussed and results on implementation of measurement procedure in banking sector are presented. It is shown how a very limited set of available data – interbank exposures and information from balance sheets and profit a loss accounts – can help in generating randomised scenarios of possible losses related to market and credit risk.

1. Introduction. The definitions of contagion in financial system can be found in Degryse and Nguyen (2004), Elsinger et al. (2003), Drehmann (2002), Wells (2004). We concentrate on contagion resulting from interdependencies between banks through interbank market exposures. The obligations that thus arise could transmit the consequences of the insolvency or bankruptcy of a selected group of banks to other players within banking sector. An undertaking with a placement that is not repaid (due to debtor default) may not perform on its obligations to other banks. This situation is termed the "domino effect", or "contagion effect". In the paper we are developing methods of contagion measurement. For convenience, we define two sorts of defaults:

– *primary defaults* – as a result of market and credit risk factors external to interbank market that can lead to bank's losses, hereafter called *primary losses*;

– *secondary (contagious) defaults* – resulting from structural dependencies between banks or financial institutions in general.

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In the article, we focus only on measuring secondary default's size.

The literature elaborating on domino effect in financial system is huge. We refer to the papers by Degryse and Nguyen (2004); Elsinger et al. (2003, 2004); Furfine (2003); Huang and Wu (2001); van Lelyveld and Liedorp (2006); Naqvi (2004); Rochet and Tirol (1996); Wells (2004). Works of Dow (2000); De Bandt and Hartmann (2000) and Hałaj (2005) (in Polish) sum up the achievements in the field of systemic risk[1] and contagion.

We will combine both Elsinger et al. (2003) and Degryse and Nguyen (2004) making use of clearing payment concept but without complicated estimation of credit and market risk in the system that is used by Elsinger et al. (2003) to build an econometric model, generating shocks to the banking system based on macroeconomic variables (so called *MacroModel*). So loss scenarios triggering defaults of banks are arbitrary like in Degryse and Nguyen (2004). We will show however how the loss scenarios can be randomised to reflect very basic suppositions about banking activity and environment like "the amount of risk taken by a bank may be learnt from minimal capital requirement (or CAR)" and "correlation in portfolios may enhance domino effect". Regulatory capital requirements of banks serve as approximation of the credit and market risk related to the observed asset structure of banks. We will focus on the problem of aggregate measures of contagion effect.

The main questions we would answer in the article are as the following.

- Does the disability to repay interbank loans in one bank cause problems with paying back liabilities in other banks? Such a transmission of problems throughout the system is hereafter called *contagion effect* or *domino effect*.
- How can balance sheet and profit and loss account data be used to obtain more accurate estimates of domino effect proneness? How correlation between assets of banks can be embedded into the model?
- How to generate reasonable shocks effecting capital of banks that may trigger or amplify contagion? Reasonable means reflecting risk taken by a bank.
- How can the contagion effect be measured for monitoring systemic risk?

2. Model. The model originates to Elsinger et al. (2003) and was simplified to be applied without need to estimate the exact loss distribution credit and market risk undertaken by the bank. The aim of the model is to find possible flows of payment between banks resulting from interbank exposures given banks' ability to pay back loans, i.e. given what they receive from other bank, where their net exposure is positive and given their current capital base and possible non-interbank market losses (or

[1]Risk affecting an entire financial system, and not just specific participants.

profits). The flow of payments is measured by a vector of so-called *clearing payments* obtained as a solution of the following equation:

$$p_i^* = \min \left\{ \left(\sum_{j=1}^{N} \pi_{ij} p_j^* + (1-\gamma) e_i - \epsilon \mathrm{Loss}_i \right)^+ ,\ \bar{p}_i \right\}, \tag{1}$$

where

- N — number of banks,
- $\bar{p}_i$ — total obligations of bank i to other banks on deposits taken,
- p_i^* — flow of funds from bank i to other banks in the system (an element of the clearing payment vector),
- π_{ij} — ratio of deposits taken by bank i from bank j to total obligations of bank i on interbank deposits,
- e_i — capital base of bank i,
- γ — "bankruptcy threshold", i.e., percentage of capital base of bank i such that, where its loss reduces equity to γe_i, bank i becomes bankrupt,
- Loss_i — losses arising from market and credit risk incurred by bank i,
- $\epsilon \in \{0, 1\}$ — indicates that the analysis considers market and credit risk losses.

More details on original specification of clearing payment equation can be found in Elsinger et al. (2003) and on the particular form (1) in Hałaj (2005). We will elaborate on ways of generating loss scenarios Loss in section 3 that is devoted to the range and the availability of date used in the model. There is also a problem with ambiguity of definition of bankruptcy threshold and we will comment on this matter in the following subsection.

Bankruptcy. Bankruptcy is usually related to the level of bank's capital. Such a conclusion is supported by financial and economic theory that tries to answer the question about conditions in which social costs of default are the lowest and shareholder value is the highest. Even though in banking acts there are strict definitions of situations when bank defaults, in many real life cases the boundary may be blurred. It is clear that purely theoretically, capital of bank cannot be lower then 0. In fact the main indicator of bankruptcy is *capital adequacy ratio* (CAR) falling below 8%. However, banking supervision may be concerned if CAR is falling dramatically or is only slightly higher than 8%. It may require that banks undertake rehabilitation process and improve their capital base[2]. On the other hand, systemicly important bank may be allowed to operate even if its CAR falls accidentally below 8% and there are reliable guarantees that it will succeed in rehabilitation process. Since the bankruptcy level is not strict it seems reasonable to test domino effect under different definitions of bankruptcy. We propose 3 definitions that will be used hereafter:

1. ("0%" case) if capital drops below 0 ($\gamma = 0$) – in this way we obtain the lowest bound for estimation of domino effect spreading out through interbank channel;
2. ("50%" case) if capital drops below 50% of its current level ($\gamma = 0.5$) – such losses could evoke actions by banking supervision since they may very significantly afflict capital adequacy; it is assumed that bank can pay back liabilities till its capital decreases by half. Than losses are fully transmitted to its interbank creditors, i.e. there is no loss recovery;
3. ("8% CAR" case) if capital adequacy ratio falls below required 8% – bank becomes insolvent in regulatory sense; analogously like in a case 2., bank repays loans if only its CAR stays above 8%. This is equivalent to a case with $\gamma = 0$ and $e := e - 8\% \cdot (\text{risk\_weighted assets})$.

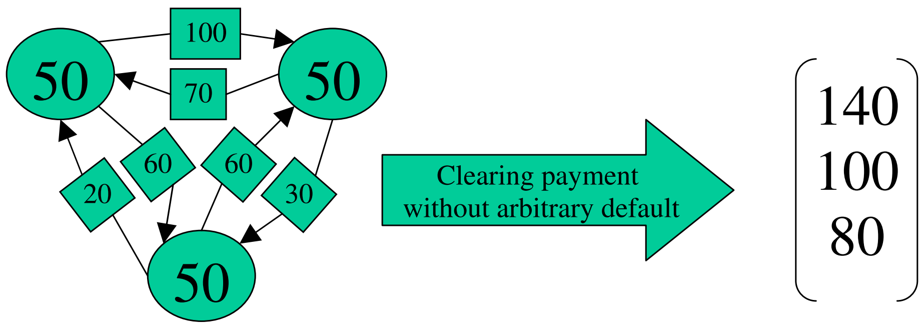
Example. Clearing payments method of contagion detection does not even require arbitrary defaults. It indicates whether there is enough capacity for solvency in the system, i.e. what happens if all interbank loans become due at the same time. Figure (1) shows how clearing payments works.

3. Data.

1. Interbank market exposures – Polish central bank has complete set of bilateral exposures of banks on the domestic market, so unlike in Austrian bank we do not need to estimate it. Most of them are very short-term loans. However, there is a small amount with residual time longer than 1 month. For each bank we summed up exposures for all maturities and calculated netted interbank exposure. For each pair of banks we got therefore a difference between deposits taken by a given bank and obligations to its counterpart.
2. Capital base of banks (capital buffer) – the sum of equity capital, subordinated debt, current period earnings and earnings pending confirmation.
3. Data for generating loss scenarios:

[2]Polish Banking Act states that Commission for Banking Supervision may require rehabilitation process if bank reports a loss exceeding 50% of its capital. If rehabilitation fails within next 6 months Commission may allow for takeover or liquidation.

Figure 1: Contagious default in a system consisting of 3 banks



Remark: Numbers in ellipsis indicate amounts of banks' capitals and rectangles – amounts of interbank liabilities. Clearing payments vector indicates that in case all liabilities in this system are due, one of bank defaults since it has to repay 160 units and has only 140 units. There is risk of contagion even in case of no trigger event unless the bank will supplement its capital.
Source: own results

- In an ideal situation one could wish to have macroeconomic model (MacroModel) for forecasting or projecting financial results of banks. It should link the macroeconomic variables and the assets/liabilities structure of particular bank with possible results of a bank and should provide an analyst with distribution of results in the horizon of analysis.
- It may happen that lack of reliable data or insufficiently long time series exclude construction of well-specified, statistically significant MacroModel. But still it may be possible to estimate market and credit risk model for forecasting loss distribution from market and loan portfolio.
- Even in a case, when the central bank does not have access to sufficiently large database of loans, it may still be reasonable to consider some very rough proxies for market and credit risk. Any relaxation of arbitrariness in choosing the defaulting banks may help to understand the shape of distribution of contagion losses. We propose to use regulatory *minimum capital requirements* (MCR) that are reported to supervisory authorities. It shows in a very approximate way how much risk has the bank taken. The more risky assets it possesses the higher is MCR and the more volatile financial results can be. At least one can expect that the distribution function is more skewed to the right. There are at least 3 advantages of such an approach. Firstly, MCR is the proxy for differences in probability

of extreme loss events between banks. The study of extreme events is important since they are usually the only trigger of contagion in this type of models[3]. Secondly, the scenarios in the domino effect stress-test can be parametrised by one parameter. The analyst has only to choose appropriate class of distributions with one free parameter from which the losses can be drawn independently. Thirdly, the analysis becomes very simple.

On the other hand, one has to keep in mind that loss distribution obtained by means of MCR is the very preliminary approximation of bank's losses. Losses resulting from market and credit risk are far more complex function of many economic factors and endogenous features of a bank. There is also a serious problem of expiry mismatch between interbank loans and assets that bear credit and market risk not related to interbank loans (household loans, investment loans, commercial papers, treasury bills, listed stocks, off-balance sheet items, etc.) that we use for justification of our loss scenarios. Losses from non-interbank exposures realise usually in far more longer horizon then stable structure of interbank loans can be expected.

- The picture of losses in banking system is far from being complete unless we add a measure of common / similar reactions of banks to economic factors (EF) effecting banking environment and to performance of other banks (P) like measures of reputation or herding behaviour. We elaborate on this a little bit more.

(EC) Such factor like economic growth, inflation, interest rates, indebtedness of the economy may change banks' macroeconomic environment in a similar way. For instance, if economic growth decelerates then firstly banks grant less loan and capacity for generating profits declines and, secondly slumping interest margins decrease rates of return from loan portfolios in general. On the other hand, after soaring economic growth eventually cools down, rate of irregular loans in all banks may increase since banks may equally adopt less restrictive lending policies during good times.

(P) Bank relies on reputation. If one bank fails to meet its liabilities it is more likely that clients of other banks may require higher risk premiums from other banks. Interbank market spreads may rise in general or if failure was very surprising and severe it could trigger mass withdrawal of deposits in the system. This type of contagion is very hard to model since there is scarcity of data for estimation or calibration.

Hence, banks may react in a common way to some economic parameters. MacroModel should capture correlation but what if no MacroModel is available? We propose three different solution based on commonly available

[3] Contagion through interbank market.

data: time series of pretax profit, of irregular loans and of ratio of irregular loans to total volume of loans.

So to generate losses we need a class of distributions parametrised by (CAR) and with covariance matrix constructed from time series proposed above. We than obtain multivariate distribution with marginal probabilities from a given parametric class.

4. Loss scenarios. Hałaj (2005) propose a method for generating random scenarios of losses based on the minimum capital requirements that is reported by banks. We assumed firstly after Hałaj (2005) that the primary loss of a bank has exponential distribution with parameter chosen in such a way that probability of loss exceeding reported minimum capital requirement is equal to 99%. Minimum capital requirement serves as a proxy for distribution of losses and we assume that capital covers 99% of losses (as in Basel II regime). Thus distribution is controlled by means of only one parameter. It makes the simulation very simple.

Then the following modifications were proposed[4]:

1. The primary loss is modelled indirectly. We assume that pretax profit has a normal distribution[5] with mean in average historical pretax profit $\mathcal{E}[\text{PretaxProfit}]$ and variance such that $\mathbf{P}(\text{PretaxProfit}_i \geq -\text{MCR}) = 1 - \alpha$, i.e. $\mathbf{P}(\text{Loss}_i > \text{MCR}) = \alpha$, MCR_i is minimum capital requirements of bank i. A parameter α is set to 0.01 or 0.05. So standard deviation of Loss_i is set to σ_i satisfying $\Phi\left(\frac{\text{Loss}_i - \text{PretaxProfit}_i}{\sigma_i}\right) = 1 - \alpha$, where Φ is cumulative standard normal distribution. It means that we assume that financial results of a bank have mean equal to historical mean $\mathcal{E}[\text{PretaxProfit}]$ and losses does not exceed MCR in 99% of cases. Results of calculation of loss distribution in the system are presented on figures (10) and (8).

2. Correlation in financial results may enhance propagation of domino effect in the system. Replacement of exponential distribution by normal distribution can make modeling of the correlation simple. Namely, we take historical data of pretax profits of banks and construct covariance matrix C of pretax profits. Under assumption that profits are correlated like the empirical correlation shows, we replace variance matrix
$$\begin{bmatrix} \sigma_1^2 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sigma_n^2 \end{bmatrix}$$

[4]**Notation**: „**P**" denotes theoretical probability and „$\mathcal{E}$" — empirical expectation.

[5]Very simplifying assumption since usually losses related to credit risk are skewed and fatter-tailed.

by the following covariance one:

$$\begin{bmatrix} \sigma_1^2 & \dots & [r_{ij}\sigma_i\sigma_j]_{j>i} \\ \vdots & \ddots & \vdots \\ [r_{ji}\sigma_j\sigma_i]_{i>j} & \dots & \sigma_n^2 \end{bmatrix},$$

where r_{ij} is correlation between pretax profit of bank i and bank j. Comparison of results with and without correlation for Polish banking system are presented on Figures (10), (11), (8) and (9). This is a very simplified approach. Firstly, one should look for correlation directly in asset classes of banks and infer from this correlation in profits, to capture dependence of risks imbedded into assets and minimise seeming, statistical correlation. Secondly, this approach is very backward-looking and does not take into account possible economic scenarios that would influence banking sector in the nearest periods. Apart from pretax profits correlation between losses can be inferred from the proxy for credit risk which is the most important source of risk in banking. We propose to use correlation between irregular loans of banks and relation of irregular loans to total loans.

5. Measures of contagion. We measure contagion based on series of clearing payments calculated for different scenarios drawn from a given primary loss distribution. For broad characteristics of contagion we use a couple of measures of loss distribution:

1. number of contagiously defaulting banks — measure of how broadly the contagion spread across the system;

2. total loss — total amount of interbank loans that are not paid back by contagiously defaulting banks; they may lead to further defaults or not but would influence profit/loss account of other banks in the system;

3. share of defaulting banks in total assets — the share of assets of banks that defaulted in total assets of banking sector; informs whether small or large banks are prone to domino effect;

4. average CAR – mean capital adequacy ratio of all banks except primarily defaulted banks; tells how much contagion effect afflicts capital adequacy of banking system;

5. measures on distribution of losses that are obtained from simulation i.e.:

    - value-at-risk of domino effect losses — 95th or 99th percentile of total loss or share of defaulting banks in total assets or 1st or 5th percentile of average CAR;

- expected shortfall during contagion — expected total loss given the fact that contagion occurred i.e., the coincidence of interbank structure and losses resulting from credit or market risk led to at least one secondary default.

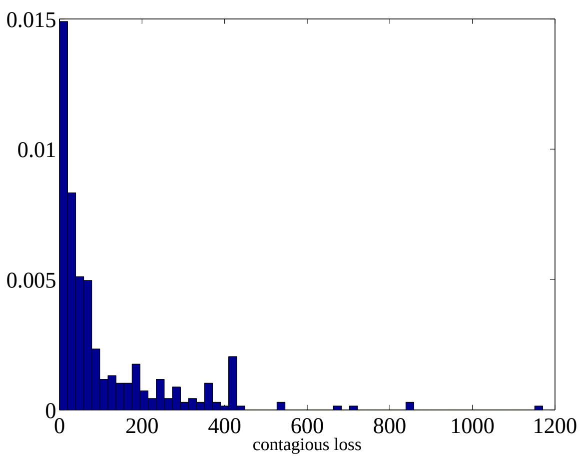
6. Simulations. We generated scenario of losses from given primary loss distribution for each bank taken into account in the simulation. Then we calculated clearing payments for the system. We repeated this step 5000 times for each distribution, i.e. we performed a kind of Monte Carlo simulation. In most cases there was no loss and the tail of distribution would not be seen. That is why we showed conditional distribution of losses, i.e. we calculated distribution of losses given secondary bankruptcy took place and presented it on figures. Fields of bars on a given figure sum up to 1 so each bar refers to probability of the loss for which the bar is plotted. So the higher and the more dense the bars are the more likely it is that losses referring to these bars occur. We are gathering general observations.

Netting. We used netted exposures in our simulation. This is justified by the fact that in case a given bank refuses to meet its obligations to other bank, its creditor can block all deposits taken from this given bank. After having looked into data we observed only a few pairs of banks with such bilateral exposures, which is not surprising. However we observed some and we checked how netting assumption changes the contagion results. We used exponential loss distribution with MCR as a bound for its 99 percentile. As figures (2) and (3) show, the difference between domino effect measured by distribution of contagious losses is negligible and can rather be an outcome of Monte Carlo approximation.

Bankruptcy level. The results of contagion in a "50%" case look significantly different than in case default happens below 0. It is not surprising but confirms that analysis should be done for different levels of capital to avoid over and underestimation of contagion risk. In a "50%" case expected shortfall measured by amount of losses was almost 1.7 time higher than in "0%" case. Figures (6) and (7) indicate that "50%" and "8% CAR" cases are not substitutes. Contagious losses generated in the case when bankruptcy occurs after CAR drops below 8% are much higher than in remaining 2 cases.

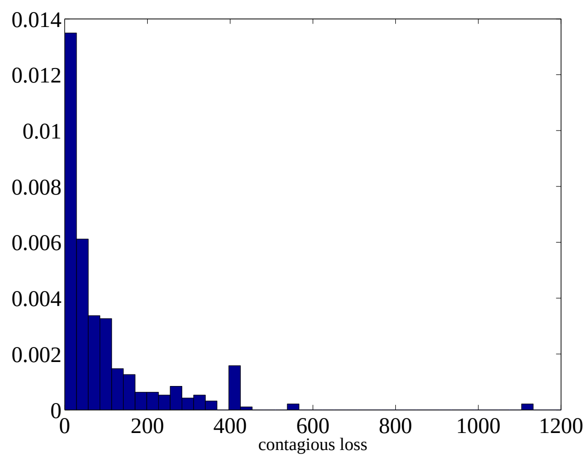
Correlation. Correlation was calculated based on quarterly data starting from Q1 of 1998. We make here a technical note. The correlation was calculated only for those banks that operated for at least 10 periods (10 quarters). Since some banks started to operate quite recently or were active only at the very beginning of period of analysis (and for example were taken over) we excluded very short time series and avoided seeming correlation. It can be seen that by taking into account correlation the number of default events decreases but mean loss increases. What is more correlation makes the *tail* of distribution of contagious losses thicker (see figure (9)). It means that huge losses are more likely — probably results of banks that are subject to

Figure 2: Distribution of unpaid liabilities of banks suffering contagious failure given default and with probability that the loss exceeds MCR equal to **95%** (exponential distribution), **without netting**, 31 Dec 2005 (in mln zł)



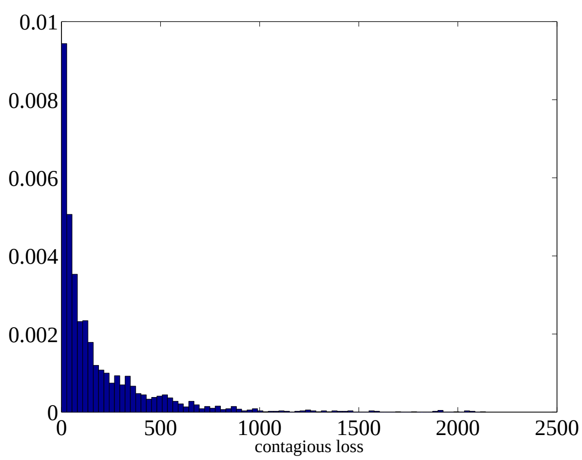
Note: default occurred in 349 cases of total 5000 scenarios. Expected shortfall in the system is equal to 111.2 mln zł.
Source: NBP.

Figure 3: Distribution of unpaid liabilities of banks suffering contagious failure given default and with probability that the loss exceeds MCR equal to **95%** (exponential distribution), **with netting**, 31 Dec 2005, (in mln zł)



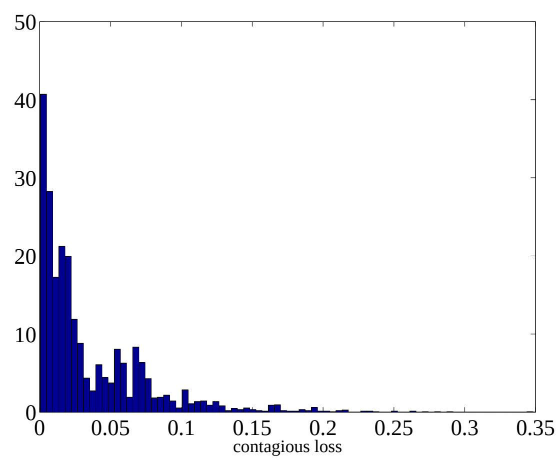
Note: default occurred in 367 cases of total 5000 scenarios. Expected shortfall in the system is equal to 100.3 mln zł.
Source: NBP.

Figure 4: Distribution of unpaid liabilities of banks suffering contagious failure given default and with probability that the loss exceeds MCR equal to **99%** (exponential distribution), default if capital drops below **50%** of initial capital, 31 Dec 2005 (in mln zł)



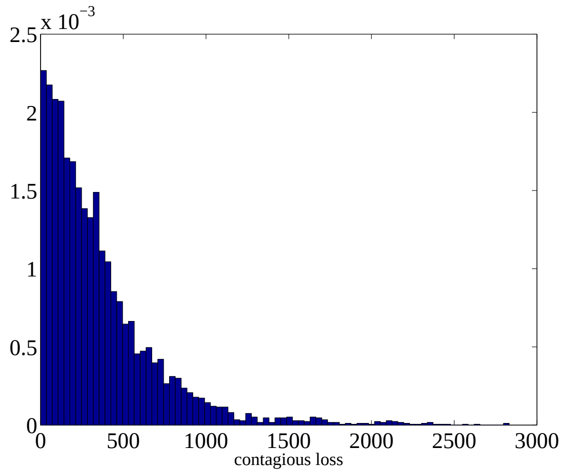
Note: default occurred in 3367 cases of total 5000 scenarios. Expected shortfall in the system is equal to 187.15 mln zł.
Source: NBP.

Figure 5: Distribution of ratio of assets of banks suffering contagious failure to total banking sector assets given default and with probability that the loss exceeds MCR equal to **99%** (exponential distribution), default if capital drops below **50%** of initial capital, 31 Dec 2005, (in mln zł)



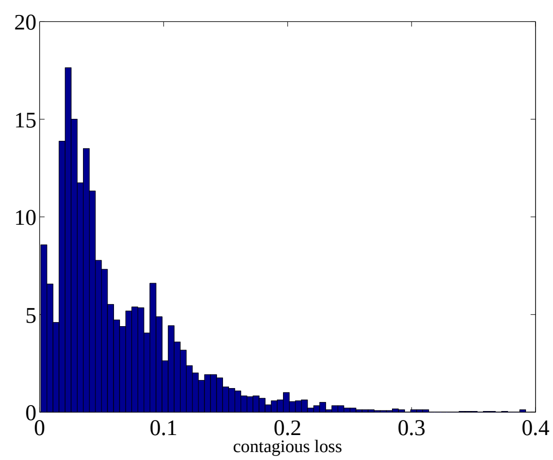
Note: Expected shortfall in the system is equal to 3.53% of total assets.
Source: NBP.

Figure 6: Distribution of unpaid liabilities of banks suffering contagious failure given default and with probability that the loss exceeds MCR equal to **99%** (exponential distribution), default if **CAR drops below 8%**, 31 Dec 2005 (in mln zł)



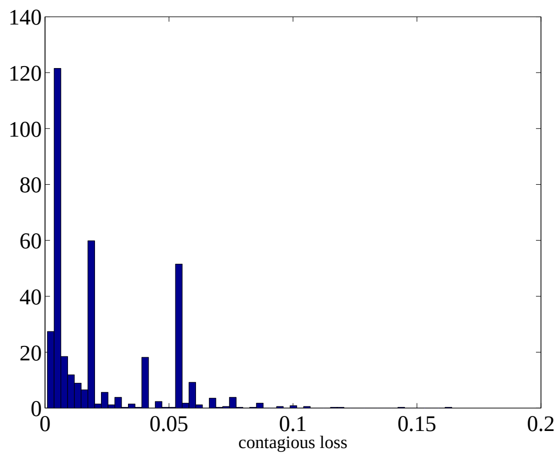
Note: default occurred in 4893 cases of total 5000 scenarios. Expected shortfall in the system is equal to 358.91 mln zł.
Source: NBP.

Figure 7: Distribution of ratio of assets of banks suffering contagious failure to total banking sector assets given default and with probability that the loss exceeds MCR equal to **99%** (exponential distribution), default if **CAR drops below 8%**, 31 Dec 2005, (in mln zł)



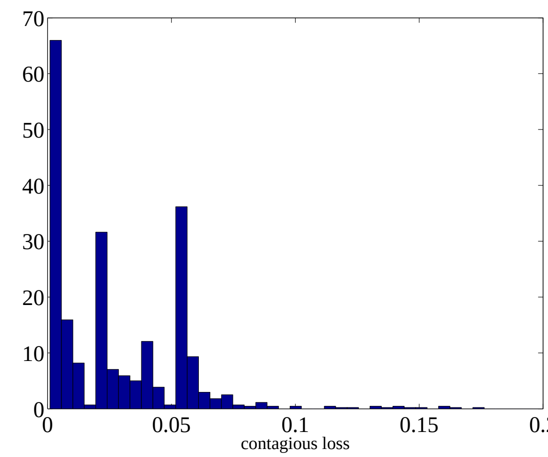
Note: Expected shortfall in the system is equal to 6.33% of total assets.
Source: NBP.

Figure 8: Distribution of ratio of assets of banks suffering contagious failure to total banking sector assets given default and with probability that the loss exceeds MCR equal to **95%** (normal distribution), 31 Dec 2005



Note: default occurred in 1235 cases of total 5000 scenarios. Expected shortfall (expected loss given default) in the system is equal to 129.9 mln zł. $\mathrm{VaR}_{.05} = 245.2$ mln zł.
Source: NBP.

Figure 9: Distribution of ratio of assets of banks suffering contagious failure to total banking sector assets given default and with probability that the loss exceeds MCR equal to **95%** (normal distribution) and bank returns are **correlated**, 31 Dec 2005

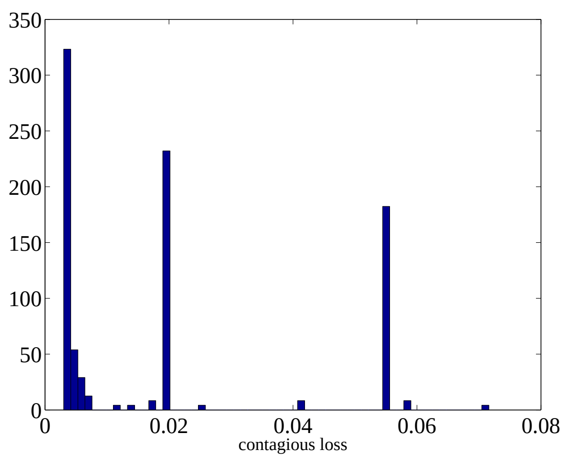


Note: default occurred in 953 cases of total 5000 scenarios. Expected shortfall in the system is equal to 161.8 mln zł. $\mathrm{VaR}_{.05} = 251.3$ mln zł.
Source: NBP.

domino effect are negatively correlated with their debtors and contagion is amplified. However, it is seen only when comparing expected shortfalls that differ significantly. VaR does not indicate any difference. It illustrates usual problem with VaR that does not show how large the losses would be in extreme cases. It gives only lower bound for them.

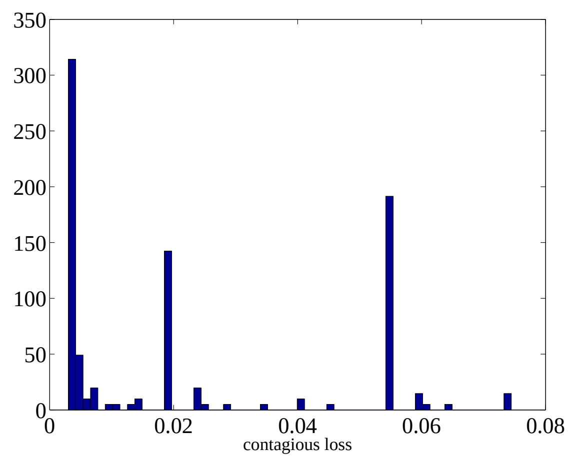
Capital adequacy ratio. As a point of reference for current capital adequacy in the system we calculated average CAR before simulation for those banks whose CARs stayed in between 8% and 50%. We did not include all banks since there are banks with extremely high CAR (e.g. start-ups) or banks that terminated activity but still report their financial data to supervisory authorities and have CARs significantly lower then 8%. These outliers would spoil the capital adequacy. Average CAR for eligible banks amounted to 14.88% which is quite high. Since we wanted to measure pure impact of contagion on solvency in the banking system, we calculated average CAR after each scenario of primary losses in a special way. We subtracted contagious

Figure 10: Distribution of ratio of assets of banks suffering contagious failure to total banking sector assets given default and with probability that the loss exceeds MCR equal to **99%** (normal distribution), 31 Dec 2005



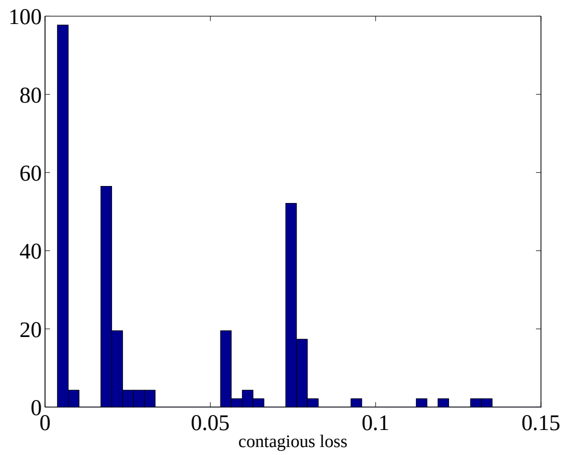
Note: default occurred in 211 cases of total 5000 scenarios. Expected shortfall in the system is equal to 76.6 mln zł. $\text{VaR}_{.01} = 100.1$ mln zł.
Source: NBP.

Figure 11: Distribution of ratio of assets of banks suffering contagious failure to total banking sector assets given default and with probability that the loss exceeds MCR equal to **99%** (normal distribution) and the bank return are **correlated**, 31 Dec 2005



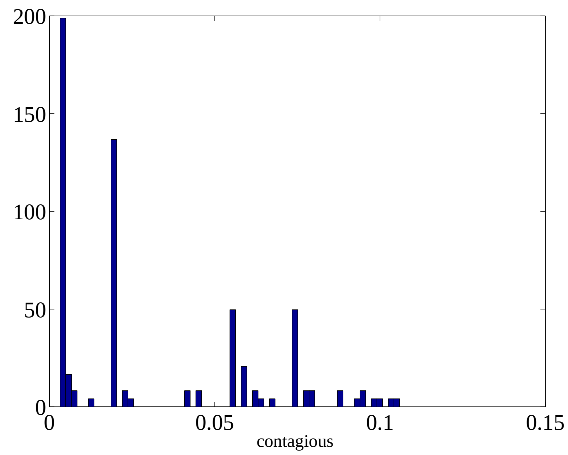
Note: default occurred in 171 cases of total 5000 scenarios. Expected shortfall in the system is equal to 90.4 mln zł. $\text{VaR}_{.01} = 102.1$ mln zł.
Source: NBP.

Figure 12: Distribution of ratio of assets of banks suffering contagious failure to total banking sector assets given default and with probability that the loss exceeds MCR equal to **99%** (normal distribution), **correlation by irregular loans** 31 Dec 2005



Note: default occurred in 140 cases of total 5000 scenarios. Expected shortfall in the system is equal to 144.5 mln zł. $\text{VaR}_{.01} = 105.5$ mln zł.
Source: NBP.

Figure 13: Distribution of ratio of assets of banks suffering contagious failure to total banking sector assets given default and with probability that the loss exceeds MCR equal to **99%** (normal distribution) and the bank return are **correlation by ration of irregular and total loans**, 31 Dec 2005

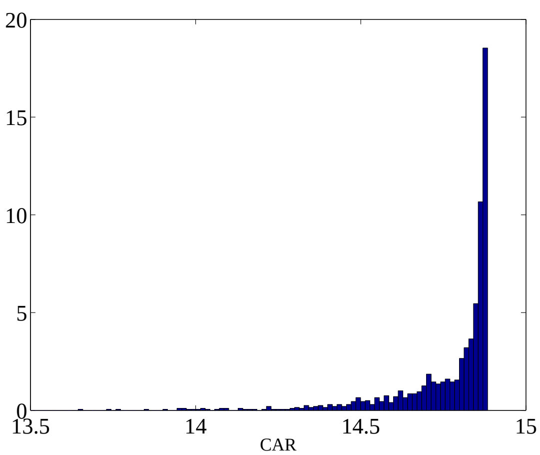


Note: default occurred in 141 cases of total 5000 scenarios. Expected shortfall in the system is equal to 112.4 mln zł. $\text{VaR}_{.01} = 87.1$ mln zł.
Source: NBP.

losses from capital of banks that were creditors of secondly defaulted banks and kept capital of primarily defaulted banks unchanged. Then we recalculated CARs for every bank that was eligible before simulation. Figures (14) and (15) show significant differences in tails of average CAR for "0%" and "8% CAR" cases after calculation of domino effect with correlation inferred from ratio of irregular and total loans. In a "8% CAR" case capital adequacy of banks is obviously effected stronger but even in the worst cases the system remains solvent.

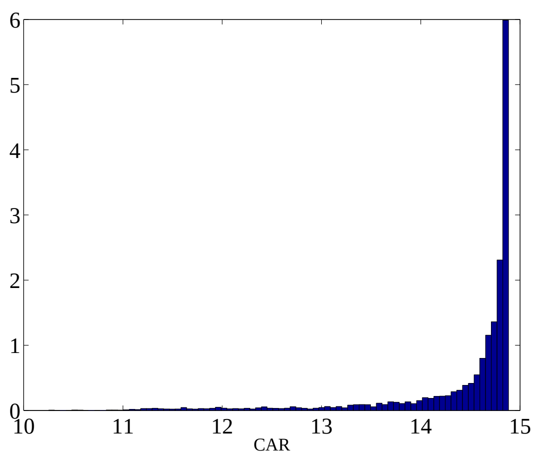
The analysis is very sensitive to the level of probability set for extreme events. Figures (8) and (9) show significantly higher possible domino effect losses in a case where probability of primary loss exceeding MCR is 5% than in case of 1% probability (see figures (10) and (11)).

Figure 14: Distribution of average CAR given default and with probability that the loss exceeds MCR equal to **99%** (normal distribution), **correlation by ratio of irregular and total loans** 31 Dec 2005



Note: $\mathrm{VaR}_{.01} = 13.59$, $\mathrm{VaR}_{.05} = 13.88$, $\mathrm{VaR}_{.1} = 13.97$
Source: NBP.

Figure 15: Distribution of average CAR given default and with probability that the loss exceeds MCR equal to **99%** (normal distribution), the bank return are **correlated like ratios of irregular and total loans** and bankruptcy takes place if CAR of a bank drops below 8%[1], 31 Dec 2005



[1] It is assumed that bank pays from its capital till its CAR stays above 8%; if it surpasses the threshold it defaults and recovery rate is set to 0.
Note: $\mathrm{VaR}_{.01} = 10.28$, $\mathrm{VaR}_{.05} = 10.49$, $\mathrm{VaR}_{.1} = 10.66$
Source: NBP.

7. Conclusion.

The general conclusion is that domino effect analysis can be done with simple loss scenario generators like one- or two-parameter distributions if there is not available any complex MacroModel for projecting or predicting results and losses. Parameters can be calibrated based on pretax profits, minimal capital requirements and irregular loans. It is reasonable to test domino effect for different bankruptcy levels and assess it with different measures. It will lower the risk of under- or overestimation of contagion effect.

However, results of models of this kind, used for estimation of the size of solvency contagion have to be treated with caution. Firstly, there is evident maturity mismatch between interbank exposures and these asset item like housing loans or securities that are basis for loss scenarios related to market and credit risk. It forces us to make a strong assumption about stable structure of interbank exposures. If there were rumors that the bank may face severe losses the interbank market would probably react very fast. Secondly, the method can easily lead to under- or overestimation of contagion risk. Usually events triggering contagion are extreme but there is not enough data for estimation of tails of credit and market loss distribution. On the other hand, clearing payments may be a very powerful tool for detection of liquidity contagion risk, since only very short-term exposures would be modeled and no maturity mismatch would take place.

It is difficult to compare the usefulness of different ways of loss scenario generating and different contagion measures that where presented. Domino effect should rather be tested by means of as many of them as possible. It is an analyst choice which triggers of loss events she wants to emphasise and what kind of domino effect outcomes she wants to measure. It may be interesting to ask about the size of domino effect in absolute terms or in relation to banking sector assets for intertemporal comparisons. The central bank and supervisory authority may want to know whether domino effect can essentially harm capital adequacy of banks or – from other point of view – how strong the shocks should be to pull banks' capital adequacy ratios below required 8% solvency threshold. It would be a kind of robustness analysis.

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