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A simulation approach to distinguish risk contribution roles to systemic crises

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Abstract

The last financial crisis has shown that large banking crises pose a highly dangerous risk to both the real economy and public finances. Reducing that risk has become a priority for regulators and governments, but the debate on how to deal with it remains open.

Contagion plays a key role: domino effects can turn a relatively small difficulty into a systemic crisis.

It is thus important to assess how contagion spreads across banking systems and how to distinguish the two roles played by 'lighters' and 'fuel' in the crisis, i.e. which banks are likely to start financial contagion and which have a 'passive' role in just being driven to default by contagion.

The aim of this paper is to propose a methodology for distinguishing the two roles, and for assessing their different contributions to systemic crises.

For this purpose, we have adapted a Monte Carlo simulation-based approach for banking systems which models both correlation and contagion between banks.

Selecting large crises in simulations, and finding which banks started each simulated crisis, allows us to distinguish 'primary' and 'induced' defaults and fragility, and to determine the contribution of individual banks to the triggering of systemic crises.

The analysis has been tested on a sample of 83 Danish banks for 2010.

Keywords: Risk contribution, systemic crisis, banking system.

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1. Introduction

Banking crises are not a new phenomenon, but systemic banking crises are a major risk for an open, linked economy. Systemic risk basically involves two main components: the financial distress of single institutions and contagion between banks. Even a single institution can trigger a financial crisis if its overall loss is large enough. On the other hand, interlinkages in actual banking systems can act as a contagion channel for default. Moreover, asset portfolios of banks acting in the same market are correlated, so that during valleys of business cycle, fragility is a common problem for a number of banks, and the risk of a banking crisis is evident in these conditions.

Contagion is caused by an initial default event that subsequentially spreads through the interbank channel, inducing other banks to default. In this framework, a primary default basically relies on losses coming from customer loans. The extent of these faiulures or downgrading could be so large to induce the failure of the bank and, via the interbank interlinkages, to weaken the connected financial institutions to the point of inducing their default. In other terms, a single financial institution may act either as 'lighter' or as 'fuel', i.e. it can induce the crisis or being induced to default by the crisis. A way to better prevent a systemic crisis and its consequences is to distinguish between these two roles.

The aim of this work is to propose a methodology for analysing the two roles and assessing the different risk contributions of a financial firm to systemic crises.

For estimating the contributions of individual banks, we follow the approach for simulating banking systems in De Lisa et al. (2011), known as SYMBOL (Systemic Model for Bank Originated Losses). Basing our analysis on this model we obtain the excess losses (i.e. the losses over the capital buffer) of each defaulted bank in a set of simulated crises. Computing risk contributions using simulated data has some advantages. In particular, such a methodology allows us to consider a variety of bank default events, which is evidently not possible if we were to consider just historical defaults. Through simulations we can handle sufficient data to proxy the tail of bank's loss distribution both for a single bank and for the aggregate system. Hence, we can distinguish large (systemic) crises from smaller ones, and proxy the systemic risk contribution for each crisis category.

Moreover, by comparing simulations with and without contagion (maintaining the same random seed in each run), we can verify which banks originate the crisis, thus distinguishing between 'primary' and 'induced' defaults and fragility. To do this, we calculate different systemic risk contribution measures to capture the total shortfall it is expected the whole system would experience, given the failure of a single institution.

The analysis has been tested on the Danish banking system using 2010 data provided by Bankscope for a sample of 83 banks, covering about 92.8 % of all the assets in the Danish banking system[1].

[1] Source: ECB http://www.ecb.int/stats/money/consolidated/html/index.en.html

The rest of this document is structured as follows: section 2 outlines the main approaches to the evaluation of systemic risk contributions proposed in the recent literature, section 3 presents the methodology we use in our analysis, section 4 discusses the sample data and the results we obtained, and section 5 concludes.

2. Systemic risk contribution measures

The literature on financial systemic risk has well developed in recent years, either in a theoretical perspective and in an empirical one, developing different approaches to measure systemic risk contributions.

Acharya et al. (2010) propose a measure called Systemic Expected Shortfall (SES), i.e. the expected shortfall of a bank conditional to the distress of the system as a whole:

$$SES_{it} = E(r_{it} \leq r_{it}^{*} \left| R_t \leq R_t^{*} \right.)$$

where r_{it} nd R_t denote the returns of the individual bank *i* and the stock market, respectively, and r_{it}^{*} and R_t^{*} are the target values of these variables. The authors use daily stock and market returns. If the systemic event in the model $R_t \leq R_t^{*}$ is thought as an extreme tail event, it is possible to define the worst *q* percentage market outcomes at daily frequency as R_q^{worst}. Acharya et al. (2010) define the so-called Marginal Expected Shortfall (MES) as the expected net equity return of bank *i* during some fixed percentage market worst days:

$$MES_{it}^{q} = E(r_{it} \left| R_q^{worst} \right.)$$

In this way the systemic crisis threshold is set in terms of Value at Risk (VaR): MES is thus refered to that part of systemic risk that affects each single bank.

Another approach for assessing the contributions of individual banks to systemic crises is the CoVaR, proposed by Adrian and Brunnermeier (2009). This is the Value at Risk of the financial system (denoted by *j*) conditional on some event $\mathbb{C}(X_i)$ of institution *i*. CoVar is implicitly defined as:

$$Pr\left(X_j \leq CoVar_q^{j|\mathbb{C}(X_i)} \left| \mathbb{C}(X_i) \right. \right) = q$$

where *q* is the selected probability level. CoVaR is a risk measure that estimates the risk contributionof a single institution to the system risk as the VaR of the total financial sector conditional to an event (distress) of that institution. This methodology has been recently applied in several studies, e.g. in Van Oordt and Zhou (2010), Roengiptya and Rungcharoenkitkul (2011), and Lopez-Espinosa et al. (2012). The contribution of institution *i* to the system *j* is denoted by ΔCoVar. This is defined as the difference between the VaR of the financial system conditional on the distress of an individual bank *i* and the

VaR of the financial system conditional to the "normal" state of the same considered bank, where a proxy for the normal state is the median:

$$\Delta CoVar_q^{j|i} = CoVar_q^{j|X_i = VaR_i^q} - CoVar_q^{j|X_i = median_i}$$

However, ΔCoVar has the drawback that it is not possible to distinguish whether the contribution is casual or driven by a common factor. In other words, this measure do not distinguish causality effects from correlation effects.

As noticed in Suh (2011), these studies no not explicitly define the default event, which makes it difficult to measure an overall systemic risk level. For example, Acharya et al. (2010) define the systemic risk by using worst market outcome events. In contrast, some other studies provided an explicit definition of default events. Huang, Zhou, and Zhu (2011) propose a systemic risk measure called the distress insurance premium, (DIP), which represents a hypothetical insurance premium against systemic financial distress. The systemic risk of the banking sector is the risk neutral expectation[2] of the total loss in the system L exceeding a certain threshold level $L_{\min}$

$$DIP = E^Q(L \mid L > L_{\min})$$

where $L = \sum_{i=1}^{N} L_i$ is the sum of the losses of all the N banks in the system.

DIP is a risk measure closely related to MES, but refering to a prefixed threshold instead of a VaR.

Individual risk contributions are then obtained as:

$$\frac{\partial DIP}{\partial L_i} = E^Q(L_i \mid L \geq L_{\min})$$

A different approach to asses the risk contributions of banks is the 'Shapley value' decomposition, first applied by Tarashev, Borio, and Tsatsaronis (2009a,b). This method considers all possible groupings of banks in the system, and derives the contributions of single banks by comparing the results of groups that include and do not include, respectively, each bank considered. The Shapley value approach has some interesting characteristics, but suffers from a serious dimensional limit: the number of different subsystems to be considered for a sample of N banks is 2^N, far too large to be actually considered. Even a small system of 20 banks needs risk values to be calculated for more than one million subsystems.

These different approaches aims at measuring the effects of large crises on single banks, thus emphasising the passive role of a bank affected by a banking crisis, or, as in the case of CoVar and ΔCoVar, the correlation between the distress of a single bank and the distress of the whole system. So,

these methods are targeted more towards the identification of systemically important institutions, using as prime source of information market equity return data.

In contrast, our study reverse the perspective, focusing on how an individual bank affects the crisis, either inducing or maintaining it. Further, in the simulations for our tests, we can use “technical" default as the distress threshold for a bank (or the system), i.e. the case where the losses of the bank are higher than its total capital (excess losses are greater than zero), and then sum the excess losses to measure the total loss for the system.

3. Methodology

Our analysis is based on simulations of the banking system behaviour that depends on actual data for each considered bank, in particular the dimension, asset riskiness, capital coverage, interbank credits and debts. The simulation model, known as SYMBOL, proposed in De Lisa et al (2011), starts by estimating individual bank credit losses, generated via a Monte Carlo simulation, according to the Basel FIRB function. The average probability of default for the credit portfolio of each bank is estimated in accordance with capital requirements, while other variables (LGD, correlation, etc.) are set at their default values.

The simulated losses of banks are then compared with actual capital: whenever losses exceed capital, banks are considered to default. Values are recorded only when at least one bank defaults, so that in our exercise more than 6.3 million simulations were needed to obtain a set of simulations with 100 thousands cases where at least one bank defaults.

By appling this framework to the sample of 83 Danish banks, the simulation produces a matrix of losses of 100,000 x 83 (simulations with defaults in the rows and banks in the columns), where each element contains a zero if the bank has not defaulted, and the excess loss if it has.

As we have already mentioned, the model also considers that contagion can occur via the interbank market, in order to capture systemic linkages between banks, in addition to the fact that their assets are correlated. Whenever a bank defaults, 40 % of its interbank debts are assumed to be passed on as losses to creditor banks and distributed among them.[3]

Contagion losses are distributed following the criterion of proportionality: the proportion of loss absorbed by each ‘infected’ bank is proportional to its creditor exposure in the interbank market. Whenever the simulation shows that this additional loss makes bank’s losses to exceed its capital, that bank is also considered to default, and so on, bank after bank, until there are no more defaults.

Systemic losses are computed as the sum of excess losses over the entire bank sample.

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[2] For CoVar and for MES the expectation is taken under the objective measure.

[3] Only domestic contagion is included. Zedda et al. (2012) verified that the proportional distribution of losses does not relevantly change the expected value in simulation results with respect to more concentrated solutions.

In order to assess if a single institution plays an ignition role in systemic crises, we first take the simulations with contagion and select cases where the total loss is above a fixed threshold, say 10 % worst cases with default, (corresponding to 0.16 % of all simulations). This subset identifies the crises that can be considered as "large" or, in other words, systemic. Since the random seed in each run is the same for simulations with contagion and without contagion, we can identify which banks defaulted also before contagion, thus inducing the crisis.

We can use different metrics for assessing the risk contribution of each bank. In contrast to previous literature focusing on the effects of a crisis on single banks, as e.g. in Acharya et al. (2010) and in Huang, Zhou, Zhu (2011), the aim of this paper is to assess the contribution of a single bank to the crisis. So we have to reverse the perspective and consider the impact of a single bank default on a systemic crisis.

Hence, following the CoVar approach, conditional risk contributions can be obtained as the VaR of the whole system conditional to the default of bank *i*:

$$Pr(L > CoVar_q^{|i}\big|_{L_i>0}) = q$$

We stress that in the present study, unlike in Adrian and Brunnermeier (2009), *L* is merely the negative part of final equity value, so *L=0* means no default and *L>0* is a default and his value is the excess loss.

ΔCoVar becomes

$$\Delta CoVar_q^i = CoVar_q^{|L_i>0} - CoVar_q^{|L_i=0}$$

where we set as the 'normal case' the no-default status of institution *i*.

We can apply ΔCoVar to our simulations, both in the case where contagion does not take place and in the case where contagion occurs. This allows us to distinguish between primary defaults (due to internal losses) and secondary defaults (due to contagion effects adding to internal losses), and to assess the ignition role of banks in crises.

As in Lopez-Espinosa et al. (2012), we can adapt the MES approach, which quantifies the risk contribution as the conditional expected shortfall, by interchanging the single bank loss and the whole system loss. By switching the conditioning we address the question which institution contributes most to a crisis as opposed to which institutions are more exposed to financial crises. We calculate the expected shortfall for the system conditional to the distress of a single bank *i* as:

$$MES_T^i = E(L\big|_{L_i>0, L>T})$$

where, as previously stated for CoVar, L_i is the excess loss of bank i and $L = \sum_i L_i$ is the excess loss in the whole banking system.

As in Suh (2011), we define a differential value for the marginal expected shortfall, but changing the conditioning. We define this contribution measure as:

$$\Delta MES_T^i = E(L\big|_{L_i>0,L>T}) - E(L\big|_{L_i=0,L>T})$$

where T is the systemic loss threshold and, as for the ΔCoVar , the 'normal case' is the no-default status of institution *i*. Even in this case, ignition risk contributions can be calculated as the expected value of a large crisis conditional upon the primary default of the considered bank (primary defaults can be highlighted by comparison between contagion and no-contagion simulations).

4. Data and results

This section is devoted to illustrate an empirical application of the proposed methodology on a sample 83 Danish banks. We consider some balance sheet data for the year 2010 provided by Bankscope database. Table 1 below reports some statistics for the sample we have used for simulations. Since some balance sheet line values were not available for all the banks, whenever needed, we have estimated the missing values. In the cases where total capital was not available, we substituted it with the common equity variable as in Bankscope, while if the solvency ratio was missing we considered the average value for the whole country. The ratios for interbank debt and credit are calculated on total assets.

Table 1: Statistics on the sample of Danish banks

	Total/Average	**Lower Quartile**	**Upper Quartile**
Number of banks	83		
Total Assets (m.€)	587,385,983	187,330	1,483,781
Common equity (m.€)	31,043,710	21,592	177,717
Solvency ratio	18.04%	14.85%	18.80%
Interbank debt ratio	8.8%	0.9%	11.8%
Interbank credit ratio	9.8%	3.1%	12.4%

Source: Bankscope as of 2010

Results show that considering risk contributions only for primary defaults results in a stricter selection, revealing systematically important banks. In fact, if we focus on ΔMES, 27 banks have losses higher than 20 bn € conditional to all defaults, while just 2 banks have such losses due to primary defaults.

Similar results are obtained with $\Delta CoVaR_{90\%}$, where 58 banks have losses above the 20 bn € threshold, while only 16 exceed it when just primary distress is considered. Figure 1 and Figure 2 report these results.

Figure 1: ΔMES due to all defaults (blue bar) vs ΔMES due to primary defaults (red bar)

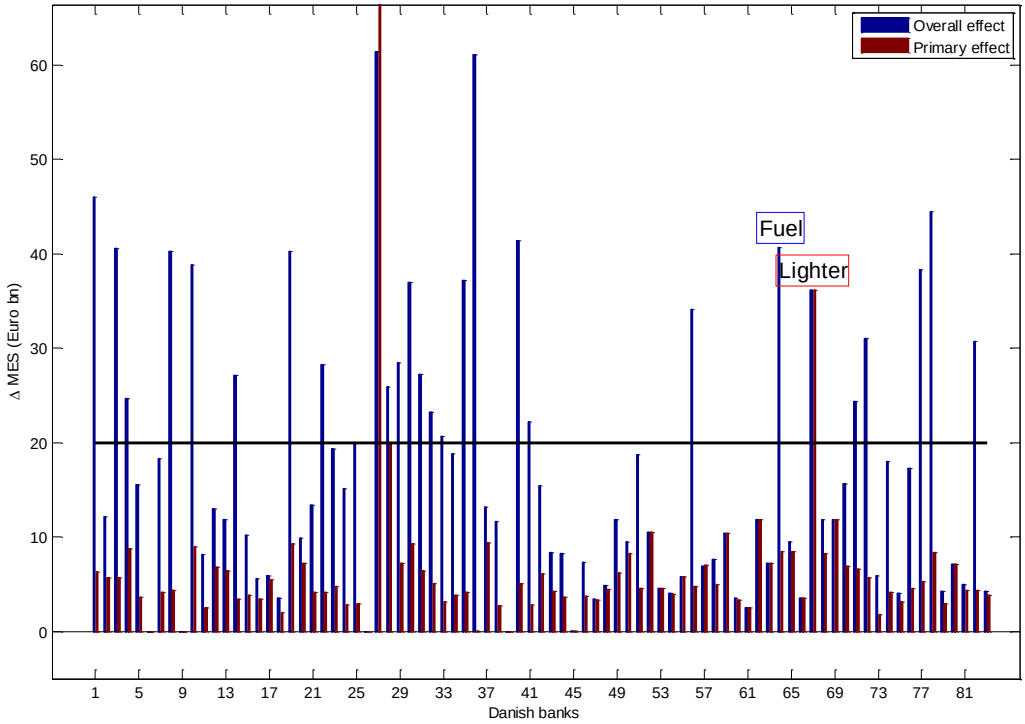
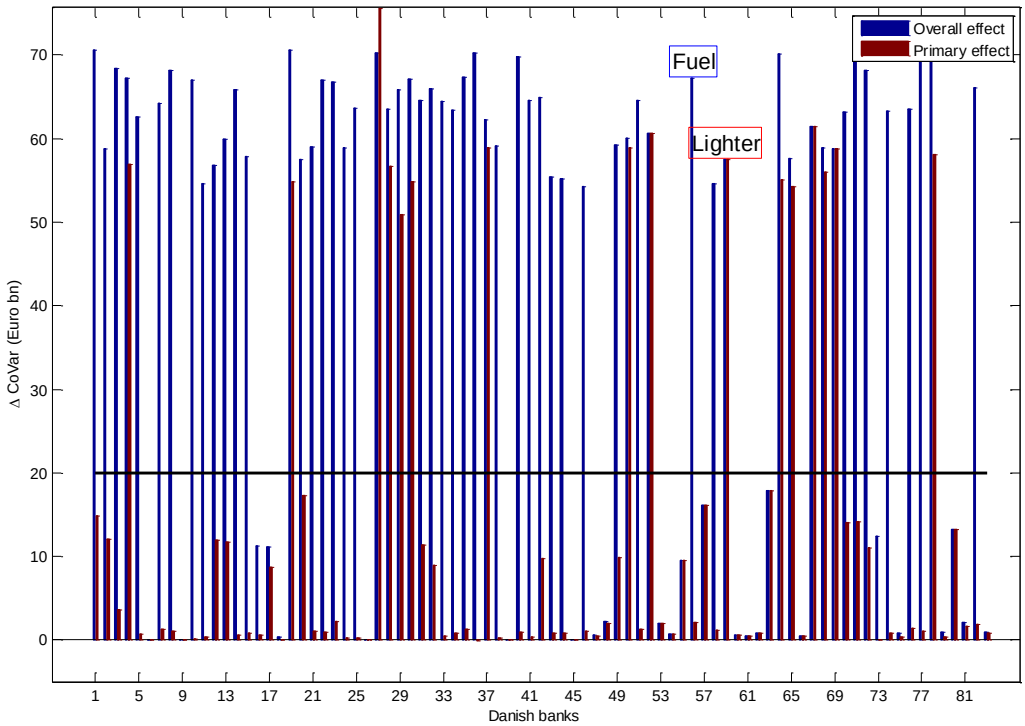


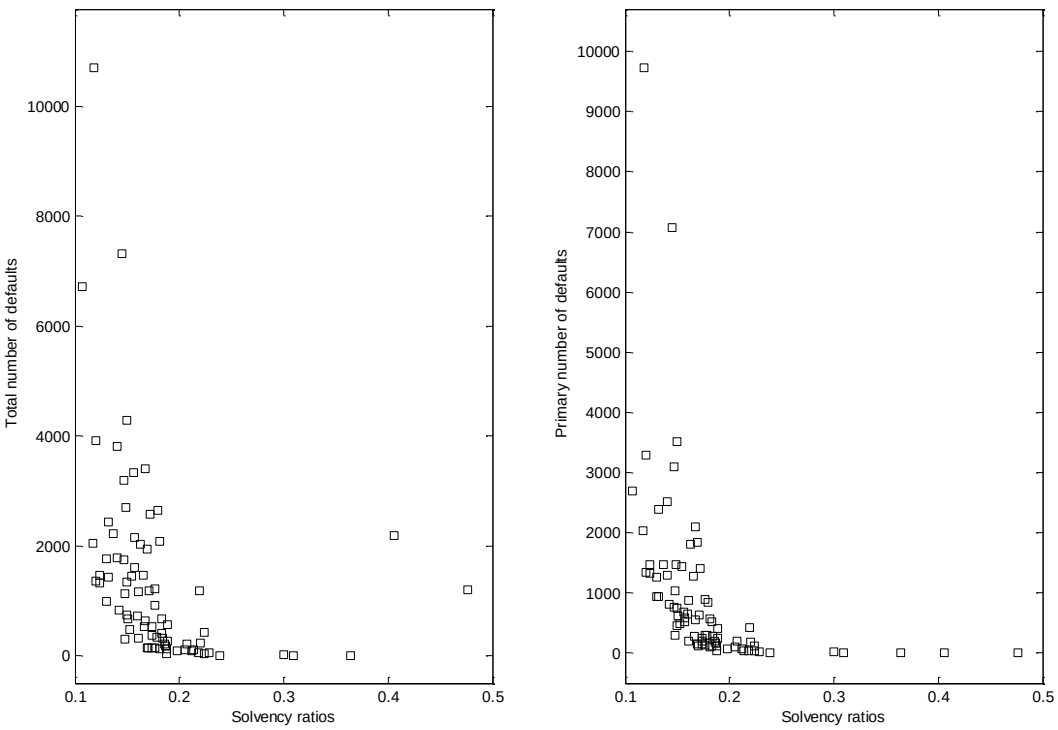
Figure 2: ΔCoVaR90 % conditional to all defaults (blue bar) vs ΔCoVaR90 % conditional to primary defaults (red bar)



The results suggest that the proposed methodology could be effective in distinguishing the different roles played by banks in a crisis. In fact, if instead of looking at all defaults we confine ourselves to primary defaults, we not only see a lowering of the whole contribution, but also notice that different

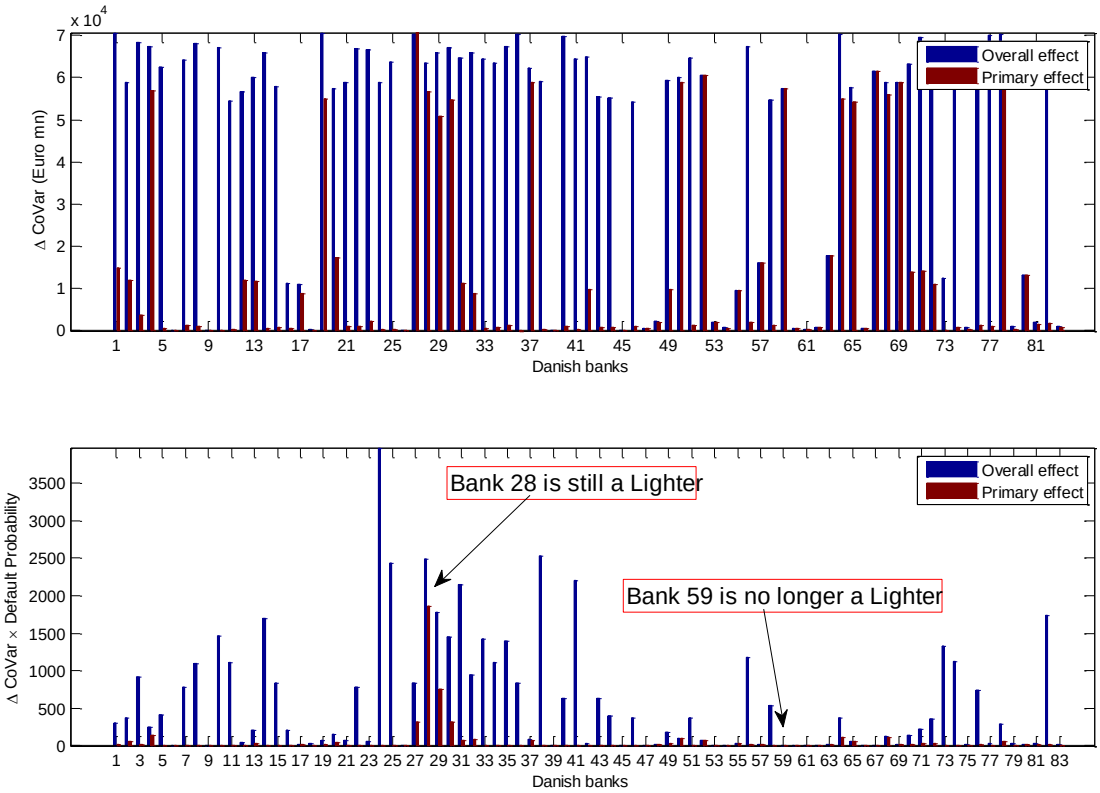
banks react differently. In particular whenever we see blue (overall contribution) and red (primary contribution) bars having approximately the same value, this would identify a potential lighter, while large differences between overall and primary effects would identify a potential fuel. We use the term potential, since being either a fule or a lighter would also depend on other aspects such as the size of losses and the probability of default, calculated as the number of times each bank defaults in SYMBOL simulations. As matter of fact, it should be noted that high values for ΔMES and ΔCoVar do not necessarily mean a high risk for the system. In fact, the larger banks are often both systematically important and highly capitalised, so that their important conditional risk contribution is counterbalanced by a low expected rate of default. Figure 3 show the effects of capitalisation on the probability of default.

Figure 3: Number of total defaults per bank vs solvency ratio (left graph) and number of primary defaults per bank vs solvency ratio (right graph)



In fact we can proxy the expected contribution to systemic crisis as the product of the differential marginal expected shortfall (or ΔCoVaR) times the expected rate of default. Even in this case the previous results are confirmed, and restricting to primary defaults gives a different outcome than if all defaults are considered. In Figure 4 we compare the ΔCoVaR results as in Figure 2 with the same values rescaled according to the probability of default. One can see that in some cases (e.g. bank 28) the role of lighter still remains even when the probability of default is taken into account, while in other cases (e.g. bank 59) the few occurences of defaults reduce the real riskness of the bank. This may be due to its high capitalization level.

Figure 4 Top panel: ΔCoVaR90 % conditional to all defaults (blue bar) vs ΔCoVaR90 % conditional to primary defaults (red bar) in Euro million; bottom panel: Expected values of excess losses conditional to all defaults (blue bar) vs expected values of excess losses conditional to primary defaults (red bar)



5. Conclusions

The risk of large banking crises has gained in importance in banking supervision. An important issue still to be addressed concerns the difference between banks responsible for starting a crisis and those only involved in it, because of some contagion effect.

So far, even relatively sophisticated methods such as MES and CoVar are not yet able to separate the two roles, since they are designed to consider the risk contribution to a banking crisis as a whole.

In this paper we have developed a method for distinguishing between the different roles of ignition and passive contagion in banking crises, modifying previous measures, in particular restricting MES and CoVar only to 'primary' defaults.

Our methodology, based on Monte Carlo simulations, considers both correlation and contagion between banks for estimating risk contributions, and it has been applied to Danish banking system for 2010

Results show that the risk contributions can be quite different, and similar values for the total risk contribution are in some cases mainly due to the 'ignition' role and in others to the 'fuel' role. This can

allow supervisors and regulators to intervene with a more focused approach, in order to act more efficiently and effectively to minimise the risk of systemic crises.

References

Acharya V., Pedersen L.H., Philippon T., Richardson M. (2010), *Measuring systemic risk*. Working paper 10-02. Federal Reserve Bank of Cleveland.

Adrian, T., Brunnermeier, M.K., (2010) *CoVaR*. Federal Reserve Bank of New York Staff Reports No 348

De Lisa R, Zedda S., Vallascas F., Campolongo F., Marchesi M. (2011), *Modelling Deposit Insurance Scheme Losses in a Basel 2 Framework*, Journal of Financial Services Research, vol. 40, n. 3, p. 123-141.

Huang, X., Zhou, H., & Zhu, H. (2011). *Systemic risk contributions*. Journal of Financial Services Research, p. 1-29.

Lopez-Espinosa G., Moreno A., Rubia A., Valderrama L. (2012), Short-term wholesale funding and systemic risk: A gobal CoVaR appoach. Journal of Banking & Finance. http://dx.doi.org/10.1016/j.jbankfin.2012.04.020

Roengiptya R., and Rungcharoenkitkul P. (2011), *Measuring systemic risk and financial linkages in the Thai banking system*. Discussion paper 02/2010. Bank of Thailand.

Suh, S. (2011). *Measuring systemic risk: A factor-augmented correlated default approach*. Journal of Financial Intermediation

Tarashev, Borio, and Tsatsaronis (2009a), *Allocating systemic risk to individual institutions: methodology and policy applications*, BIS Working Paper.

Tarashev, Borio, and Tsatsaronis (2009b), *The systemic importance of financial institutions*, BIS Quarterly Review, September 2009, p. 75-87.

Van Oordt M. and Zhou C. (2010), *Systematic risk under adverse market conditions*. Working paper. De Nederlandsche Bank.

Zedda S., Cannas G., Galliani C., De Lisa R. (2012), *The role of contagion in financial crises: an uncertainty test on interbank patterns*, EUR Report 25287, Luxembourg, 2012.

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