DECLARATORIA SULLA TESI DI DOTTORATO

La sottoscritta

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DICHIARA

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Data 27/01/2012

F.to (indicare nome e cognome) Clara Galliani

"Gli uomini si dividono in due categorie: quelli che si mettono comodi. E appassiscono. E gli altri. Io faccio parte degli altri."

(Paolo Sorrentino, Hanno tutti ragione)

To my family

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Introduction

The current financial crisis has moved the attention to some specific characteristics of financial markets.

First of all, it has highlighted the importance of developing efficiency and soundness in the financial safety net, in order to stop financial crises and to prevent consequences on the real economy. The first chapter of this work focuses on Deposit Guarantee Schemes (DGS), the safety net player that aims at protecting depositors against failure of any bank in the financial system. One of the most critical issues for a DGS is what criteria should be used to assess the risk-based contribution that each member bank has to pay to the scheme. As a starting point, is it possible to evaluate and where appropriate revise models developed in European DGSs? This chapter proposes an evaluation of the approach adopted at the Italian Deposit Guarantee Scheme, the *Fondo Interbancario di Tutela dei Depositi*. As a first step methodologies used at the Italian scheme during the period 2006-2010 are analyzed. Past performance and the application of sensitivity analysis tools reveal that such methodologies are somewhat lacking in explanatory power. For this reason I propose an alternative model for risk-based contributions based on credit default swaps (CDS) spreads. The aggregate indicator currently used in the Italian system is compared to a bank riskiness indicator obtained through the relationship between CDS spreads and bank balance sheet ratios. The analysis reveals that the two indicators have a common trend during the considered period. Results obtained in this chapter want to represent a starting point for a revision of methodologies currently adopted in EU Schemes. The analysis of the adequacy of bank riskiness indicators used in the Italian DGS as well as the investigation of the relationship between CDSs and bank riskiness indicators used in other EU DGS should be addressed in future research.

Secondly, recent bank failures confirm that government finances have to bear part of the costs associated to financial crises because of the connection between balance sheets of governments and of banks. Considering the sizeable interventions that EU governments have been providing to the banking sector since the beginning of the crisis, it is clear the importance of quantifying the effects that banking systems in troubles could have on the stability of government finances. In the second chapter I provide an estimation of the potential impact of banking crises on public finances using the SYMBOL model recently developed by the European Commission Joint Research Centre in cooperation with the Directorate General Internal Market and Services and experts of banking and regulation. SYMBOL is used to generate market scenarios in a way that is fully compliant with Basel regulation. The impact of simulated banks' failures is evaluated in four EU countries using three indicators of sustainability: the probability that public finances are hit by losses deriving from bank defaults, the distribution of costs for public finances expressed as a percentage of 2009 GDP and the probability that, due to a banking crisis hitting public finances, a Member State becomes high risk. Results are evaluated in five different scenarios that reflect five different regulatory settings (in terms of capital requirements, safety net tools and existence of contagion between banks). It emerges that there are differences among the considered countries. A sensitivity analysis conducted to quantify how much of the losses suffered by public finances is linked to the introduction of specific regulatory frameworks will be performed in future research. In general terms, the five scenarios correspond to different degrees of riskiness and contagion seems to play a crucial role in the quantification of losses hitting public finances.

Another important lesson learned from the recent financial crisis is the crucial role of interconnectedness between banks as a factor that can push the effects of bank defaults to extreme levels. One bank in distress can compromise the ability to repay obligations of its creditor banks, thereby inducing a more general crisis that spreads from the banking system towards the real economy. Several empirical and theoretical studies have focused on the role of the interbank market in causing contagion in financial crises. In this regard, one frequent problem encountered in dealing with contagion risk in the banking system is that only data on interbank credits and debts aggregated at bank level are publicly available, whereas the whole matrix of interbank linkages would be needed in order to estimate systemic risk correctly. One common solution is to assume that banks maximize the dispersion of their interbank credits and debts, so that the interbank matrix (that contains interbank exposures) can be approximated by its maximum entropy realization. The third chapter tests the influence of this hypothesis by verifying if variations in the structure of the interbank matrix lead to significant changes in the magnitude of contagion. In order to do this, it's developed an algorithm that generates more concentrated interbank matrices. Using Monte Carlo simulations, results obtained with the maximum entropy approximated matrix are compared with those obtained from more concentrated matrices. Numerical experiments, performed on samples of banks from four European countries, highlight that concentration in interbank loans does affect results but that, when considering the probability distribution of losses, even significant changes in the interbank matrix do not deeply affect results. For future developments, it would be worth performing a sensitivity analysis in order to better quantify the effects of banking systems' characteristics on financial contagion.

Chapter 1

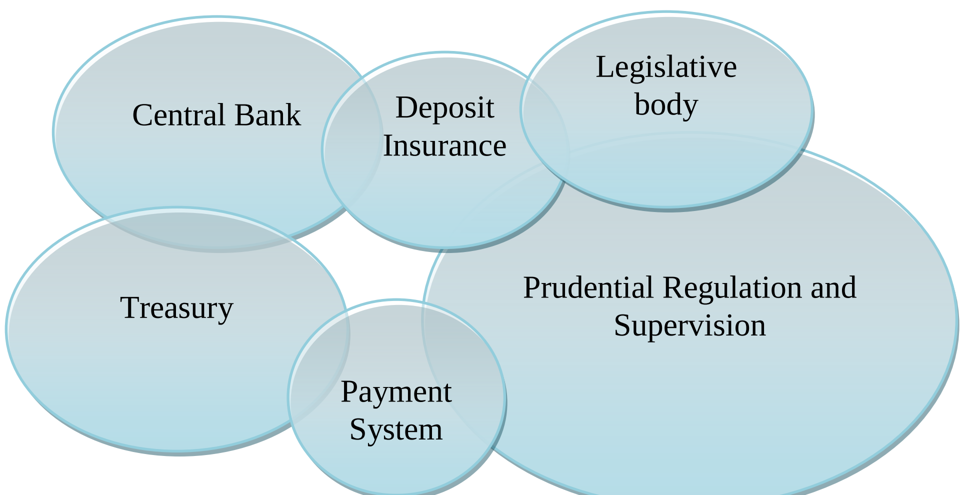
Revision of risk-based contributions using CDS spreads: application to the Italian banking system

1.1 Introduction

Deposit guarantee schemes (DGSs) are the part of the financial safety net designed to offer protection to depositors and consequently support the stability of the entire economy. They ensure depositors that, in the event of a bank's failure, they will be able to recover at least a proportion of their deposits. Of course they are not intended to deal by themselves with systemic crises generated by the failure of systemically important banks, but they need to be part of a well-designed financial system safety net where all the participants work together and cooperate (on this point please refer to the International Association of Deposit Insurers report, 2009).

As explained in Singh and LaBrosse (2011), the financial safety net has traditionally included a lender of last resort (central bank), prudential regulation (by a bank supervisor), a government department (finance ministry or treasury) and explicit deposit protection (insurance or some other form of limited guarantee). The current financial crisis has highlighted that we should also consider the role of the legislative body and non-bank regulation, since they can have a major impact on financial stability issues by supporting the other participants in the financial safety net.

Figure 1.1: *Official safety net players*



Source: *Singh and LaBrosse (2011)*

Responses to the current financial crisis and to recent changes in the financial environment (take for instance the high leverage of financial institutions and the deep interconnections among them) have meant that the mandates of financial safety net players have been extended. The primary objective in responding to a financial crisis is to stop it and prevent it from affecting the real economy. To that end, measures are taken in order to stabilize market confidence in individual banks and reduce the risk of a bank run.

As explained in Diamond and Dybvig (1983), bank runs occur when depositors rush to withdraw their deposits because they expect a bank to fail. Bank runs are caused by a combination of two factors (as explained in Ketcha, 2007): first of all the illiquidity of bank loans — the primary asset of banks — means it is impossible to sell loans quickly without a loss in value. The second factor is the ability of depositors to withdraw their deposits on demand or at short notice. Moreover, the 'first come, first served' nature of the process provides depositors with the incentive to run. A bank suffering a panic run will liquidate many of its assets at a loss and this will lead to its failure. DGSs are an instrument in the financial safety net implemented to avoid bank runs by maintaining a high level of public confidence in banks' ability to meet their obligations.

The components of a financial safety net are not immune from generating harmful effects: in particular, the existence of a DGS may create a serious moral hazard problem. With more protection being provided, market participants may find that the costs associated with riskier strategies are reduced and there is an incentive to take excessive risk. Thus, supervision and regulation are essential to control asymmetry problems and maintain confidence in the financial system. The role of supervisors and regulators is not easy, since they have to lay down rules that are able to strike a balance between safety and information asymmetry problems.

It is also clear from the current crisis that a poorly designed system of deposit protection can escalate a bank failure into a crisis, as experienced in the UK with Northern Rock.

The responses of regulators to the financial turmoil as far as DGSs are concerned have moved in the same directions in the EU and the US. Regulators agree on increasing the level of coverage, reducing (or even eliminating) co-insurance mechanisms,[1] providing quicker payouts in the event of bank failure and extending the coverage to a wider range of deposits (for a list of regulatory measures adopted in the US and the EU as of end-2008, see Schich, 2008a, b).[2]

The need for an increased level of coverage became clear after the Northern Rock episode: because of the inadequacy of the deposit insurance system, the situation had systemic implications. As a response, on 8 December 2008 the European Parliament's Economic and Monetary Affairs Committee agreed on raising the level of coverage to €50 000 from 30 June 2009 and harmonizing it at €100 000 from 31 December 2011. Countries outside the European Union raised their levels of coverage too, but, as of December 2008, there is no clear evidence of convergence among different countries.[3]

In any event, the choice of the level of coverage has to balance conflicting considerations: for instance, low levels would lead to less confidence on the part of depositors (because the DGS would make for low credibility). On the other hand, high levels could increase the risk of moral hazard. In practice, the rule of thumb generally applied is to choose the amount of coverage that allows the vast majority of depositors to be protected.

The funding mechanism is another open issue, since DGSs have to choose firstly between *ex ante* and *ex post* mechanisms and secondly between risk-based and non risk-based contributions.

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[1] Co-insurance means full protection up to a certain limit and depositors bearing the part of the loss exceeding that limit in the event of failure.
[2] Some of these points are clearly stated in the 18 principles for effective DGSs proposed by the International Association of Deposit Insurers (2009).
[3] See Schich (2008a, b) for a detailed description of adjustments in coverage levels.

In the literature there is a broad discussion about the strengths and weaknesses of *ex ante* and *ex post* funding mechanisms. The main points are summarized by Bernet and Walter (2009) in the following table:

Table 1.1*: Advantages and disadvantages of the two funding mechanisms*

	Advantages	**Disadvantages**
Ex post	• **Market discipline**: induces banks to monitor each other's activities	• **Potential payout delays**: the funds are not collected beforehand • **Procyclical effects**: commitments in poor economic situations may lead to a domino effect of bank failures, renegotiation of terms and/or collapse of the DGS
Ex ante	• **Public confidence**: prompt reimbursement of depositors possible • **Smoothed premium payments**: reduced procyclical effects • **Reduced moral hazard**: *ex ante* funding could incorporate risk-adjusted premiums • **Equitable and fair**: all member institutions (including prospective failed institutions) contribute	• **Adequate fund size**: difficult to establish a fund of sufficient size • **Appropriate premium calculation**: difficulties in devising a 'fair' calculation method • **Administrative complexity**: organisational and strategic intricacy

Source: *Bernet and Walter (2009)*

The debate about the optimal mechanism has hotted up with the current financial crisis and a consensus has emerged in favour of an *ex ante* funding procedure. Nevertheless, even if an *ex ante* mechanism ensures that funds are available, what happens when the crisis is still ongoing and extra funds are needed? (Obviously the problem of collecting extra funds is even more serious for an *ex post* funded DGS.)

The International Association of Deposit Insurers (2009) did not express a clear preference for either of the two (*ex ante* or *ex post*) funding mechanisms. It just stated that the choice must be linked to DGS needs, in the sense that all funds necessary to ensure the prompt reimbursement of depositors' claims should be available. Regarding the other funding choice, it seems that the existence of a mechanism that computes contributions corrected according to the risks taken by banks reduces moral hazard. In any event, primary responsibility for paying the cost of deposit insurance should be borne by banks (and not by general taxpayers) since banks and their clients directly benefit from an effective deposit insurance system.

As already explained in this section, DGSs are tools that are still undergoing adjustments and improvements. Current practices among DGSs have to be closely monitored, in order to identify and keep mechanisms that are useful and to abandon methodologies that are weak. The following pages analyze current practices adopted by the Italian DGS and focus in particular on the computation of risk-based contributions that allows the Italian DGS to classify banks according to their risk profile.

A careful look at the performance of the Italian DGS reveals that the methodologies used are somewhat lacking in explanatory power. I therefore propose an alternative methodology for the computation of risk-based contributions based on CDS spreads. CDSs are an evaluation of the (credit) riskiness of banks, so they can be employed as a benchmark for the calculation of any risk-based contribution to a DGS. For this reason I decided to use CDS spread data as a dependent variable and regressed balance sheet indicators on it in order to construct a risk indicator that is as close as possible to the market evaluation of riskiness in the banking system.

Literature on CDSs is relatively scarce since the CDS market enjoyed a significant increase in traded volumes only from 2004. Moreover, only a limited number of existing papers specifically examine CDS spreads in the banking sector and, among them, only one (Chiaramonte and Casu, 2010) investigates the relationship between CDS spreads and balance sheet indicators. I take as my starting point their results, which confirm that CDS spreads reflect the risk captured by bank balance sheet ratios. Thus, starting from this, I present an alternative indicator of bank riskiness constructed through regressions having CDS spreads as a dependent variable and balance sheet ratios as explanatory variables. This indicator is then compared to the one currently employed by the Italian DGS.

This model has three main strengths: first of all, it combines the CDS market and DGS procedures. As explained above, only one model relates CDSs to balance sheet ratios in the banking sector and no one has already linked this topic to practices adopted in EU DGSs.

Secondly, a model constructed in this way can be considered within EU DGSs as an alternative model to calculate risk-based contributions. This methodology is fully compliant with some of the ideal characteristics of a DGS identified by the EFDI working group[4]:

- Simplicity: a model based on CDSs is understandable by the DGS members;
- Reasonableness: the model is reasonable in terms of data gathering;
- Flexibility: the model could be easily tailored to different countries.

Finally, the model takes into account the current financial crisis, explaining changes in the relationship between CDS spreads and balance sheet ratios due to the financial turmoil.

The main weakness of the model is the partial lack of data about CDSs: data on 48 EU banking groups that issued CDSs in the period 2006-2010 are used. Results obtained from this subsample are then transferred to the Italian banking system. This implicitly assumes that the relationship between priced CDS spreads and the set of four balance sheet indicators used can be applied also to those banks not issuing CDSs. This point is a strong hypothesis since my sample of banks issuing CDSs is not a random sample (banks issuing CDSs are generally mid-tier and top-tier banking groups) and it could be dangerous to extend my results to all banks. This point could be better addressed by investigating the use of different quantities as dependent variables.

Neither am I investigating here the choice of specific bank balance sheet ratios: this work starts from the ratios currently used in Italy without analyzing their effective informative power.

These are open research questions not considered in this contribution, which aims to constitute a natural continuation of the analysis of current practices adopted in existing DGSs and put forward first ideas for a partial revision of practices that lack explanatory power.

The rest of the chapter is organised as follows: the next two sections are devoted to a detailed description of DGSs in the US and the EU, with a particular focus on changes that have occurred during the current financial crisis. Section 1.1.3 explains the methodology currently used in the Italian DGS. Section 1.2 describes the methodology used to evaluate the current Italian model and to construct the alternative model based on CDS spreads. Section 1.3 provides data on Italian banks and EU banks issuing CDSs. Section 1.4 presents results and section 1.5 sets out conclusions and points to further developments.

1.1.1 The situation in the US

CAMELS is a rating system developed in the US to classify members of DGSs according to their financial soundness. US DGSs have an *ex ante* risk-based mechanism applied by the Federal Deposit Insurance Corporation (FDIC),[5] an independent Federal Agency created in 1933 in response to the financial crises of the 1920s and early 1930s. In 2005 the FDIC’s level of coverage and reimbursement period were set at $ 100 000 (€ 80 379) and one business day.

[4] See EC JRC (2009): Possible models for risk-based contributions to EU Deposit Guarantee Schemes.
[5] http://www.fdic.gov/deposit/insurance/index.html.

Nowadays the FDIC is consolidated and principally regulated by the Federal Deposit Insurance Act (FDIA) of 1950 and by the Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991. In February 2006, the Federal Deposit Insurance Reform Act (FDIRA) became law, introducing some changes in the deposit insurance system. For instance, it merged the two existing funds managed by the FDIC (the Bank Insurance Fund, BIF, and the Savings Association Insurance Fund, SAIF) into the new Deposit Insurance Fund (DIF), increased the level of coverage for certain retirement accounts to $ 250 000 (€ 200 948), and established a range for the Fund dimension, linked to the amount of covered deposits.

The FDIC classifies DGS members into risk categories according to both capital levels and supervisory ratings. Capital levels are investigated through three capital ratios whereas supervisory ratings are assigned through a system of six financial indicators named CAMELS. The name is an acronym of the following indicators: **C**apital adequacy, **A**sset quality, **M**anagement capability, **E**arnings quantity and quality, **L**iquidity adequacy and **S**ensitivity to market risk. They contribute to building a composite indicator that, together with the capital evaluation, assign each member bank to a specific risk class.

The US system characteristics are summarised in the table below:

Table 1.2: *Characteristics of the US system*

	Description
Fund mechanism	*Ex ante*
Fund's finance	Quarterly members' contributions and earnings on fund assets
Risk-based contributions	A specific risk-based method using composite indicators is applied
Competent authority	The chartering authority closes the member and appoints a receiver (usually the FDIC)
Trigger event	Tangible equity to total assets ratio equal to or less than 2 %
Event notification	News in the local newspaper, instructions letter to all depositors
Types of intervention	Generally closed bank resolution (purchase & assumption, deposit payoff)
Pre-closing period	The FDIC works on the resolution of members for 90 days before the closure

Reimbursement	One business day

Source: *Schich (2008a, b)*

Measures taken in the US to deal with the current financial crisis go in the same direction as those applied in EU countries. As explained in Schich (2008a, b), at the beginning of the current financial crisis, the US Treasury established a two-year guarantee programme for money market fund investors, effective as of 29 September 2008, to cover fund levels as of 19 September 2008. Regarding the level of coverage and deposits actually insured, the maximum amount of insurance coverage provided per depositor per bank was raised (temporarily) from $ 100 000 to $ 250 000 in early October and in mid-October 2008 the FDIC extended the coverage of its schemes to small business deposits.

1.1.2 DGSs in the EU: functioning and regulation

At EU level, schemes are regulated by Directive 94/19/EC of the European Parliament and of the Council of 30 May 1994, later implemented by each Member State (MS) in its national regulatory framework, and by Directive 2009/14/EC. On 12 July 2010 the Commission adopted a legislative proposal for a revision of the latter Directive.

DGSs are useful instruments of prudential regulation that can promote consumer confidence and protection, mitigate banks' risk taking,[6] diminish the risk of systemic failures and, as a consequence, establish stability in the financial system. As explained in the EFDI report (2006), Directive 94/19/EC required MSs to legally set up and recognise at least one DGS by a specific deadline with the aim of achieving minimum harmonisation of deposit insurance across Europe. The few harmonised rules introduced by the Directive relate to mandatory membership for all credit institutions,[7] the exclusion of interbank deposits from coverage, a minimum coverage level

[6] See European Central Bank, 2004.
[7] Voluntary membership would lead to adverse selection or moral hazard behaviour.

of €20 000, a three-month limit for repayment with the possibility of extending it twice and information to be provided to depositors as an essential part of the guarantee itself.

What is not spelled out in the Directive is left to MSs to regulate independently. For this reason, DGS characteristics vary across Europe. As explained in Cariboni et al. (2010), in 2009 there were 39 DGSs in the 27 Member States. They are listed in the table below:

Table 1.3: *List of DGSs in the EU Member States*

Country		Name
BE	Belgium	Deposit and Financial Instruments Protection Fund
BG	Bulgaria	Bulgarian Deposit Insurance Fund (BDIF)
CZ	Czech Republic	Deposit Insurance Fund
DK	Denmark	Guarantee Fund for Depositors and Investors
DE1	Germany	Compensatory Fund of the Association of German Public Sector Banks
DE2	Germany	German Private Commercial Banks Compensation Scheme for Depositors and Investors
DE3	Germany	Protection Scheme of the National Association of German Cooperative Banks
DE4	Germany	Guarantee System of the Savings Bank Finance Group
EE	Estonia	Deposit Guarantee Sectoral Fund
IE	Ireland	Irish Deposit Protection Scheme
GR	Greece	Hellenic Deposit Guarantee Fund
ES1	Spain	Deposit Guarantee Fund for Banks
ES2	Spain	Deposit Guarantee Fund for Credit Cooperative Banks
ES3	Spain	Deposit Guarantee Fund for Savings Banks
FR	France	Deposit Guarantee Fund
IT1	Italy	Interbank Deposit Protection Fund (*Fondo Interbancario di Tutela dei Depositi*)
IT2	Italy	Deposit Guarantee Fund for Cooperative Credit Banks
CY1	Cyprus	Deposit Protection Scheme
CY2	Cyprus	Deposit Protection Scheme for Cooperative Societies
LV	Latvia	Deposit Guarantee Fund
LT	Lithuania	Deposit and Investment Insurance
LU	Luxembourg	Luxembourg Deposit Guarantee Association
HU	Hungary	National Deposit Insurance Fund of Hungary
MT	Malta	Depositor Compensation Scheme
NL	Netherlands	Collective Guarantee Scheme of Credit Institutions for Repayable Funds and Portfolio Investments

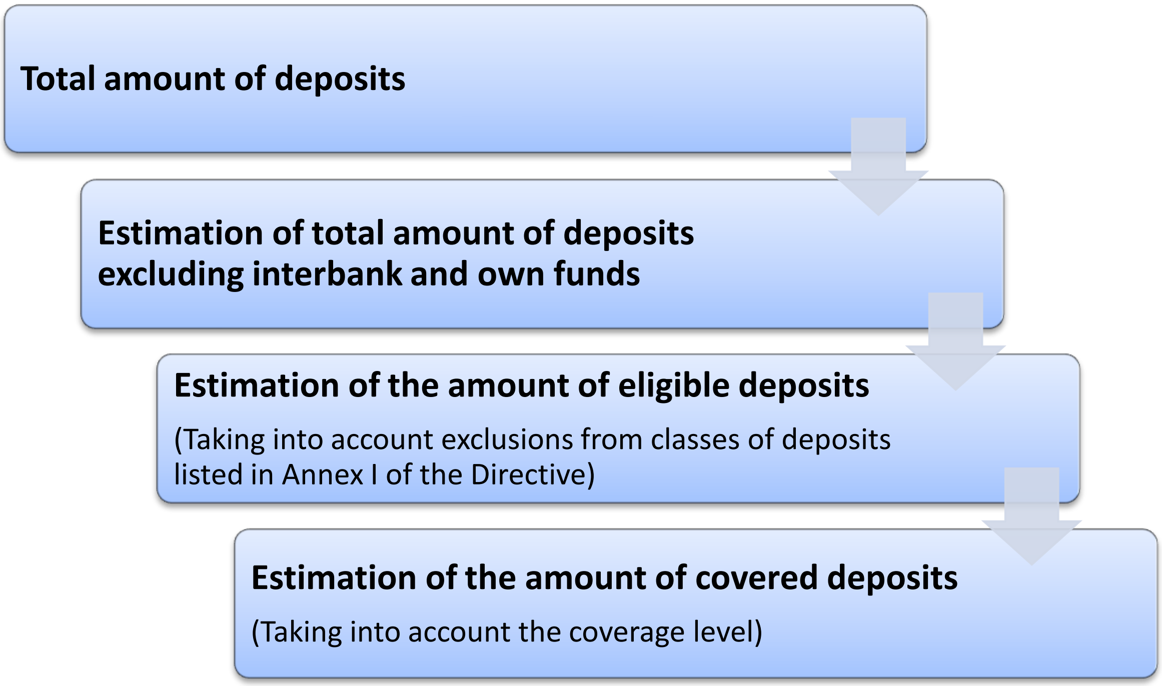
AT1	Austria	Einlagensicherung der Banken & Bankiers Gesellschaft m.b.H
AT2	Austria	Österreichische Raiffeisen-Einlagensicherung reg.Gen.m.b.H. (ÖRE)
AT3	Austria	Sparkassen-Haftungs Aktiengesellschaft
AT4	Austria	Schulze-Delitzsch Haftungsgenossenschaft reg.Gen.m.b.H.
AT5	Austria	Hypo-Haftungs-Gesellschaft m.b.H.
PL	Poland	Bank Guarantee Fund
PT1	Portugal	Deposit Guarantee Fund
PT2	Portugal	Guarantee Fund of Mutual Agricultural Credit Institutions
RO	Romania	Deposit Guarantee Fund in the Banking System
SI	Slovenia	Deposit Guarantee Scheme
SK	Slovakia	Deposit Protection Fund
FI	Finland	Deposit Guarantee Fund
SE	Sweden	Swedish Deposit Guarantee Board
UK	UK	Financial Services Compensation Scheme

Source: *Cariboni et al. (2010)*

The direct consequence of the latitude left by Directive 94/19/EC is the existence of differences among schemes. The main areas where schemes may differ are the following:

- **Covered deposits**. The procedure to compute the contribution base for a given bank is summarised in the Figure below:

Figure 1.2: *Procedure to estimate the amount of eligible and covered deposits*



Source: *EC JRC (2009) – Annex II*

The voluntary inclusion in the contribution base of items mentioned in the Directive can lead to differences among MSs.

- **Level of coverage**. Before the current financial crisis, around half of the MSs chose to guarantee the minimum level of coverage (€ 20 000), whereas other MSs opted for higher amounts (up to the maximum of around € 103 000 in Italy). Deposits insured up to the cap chosen by each country are called covered deposits. They are a subset of eligible deposits, defined as deposits for which, in the event of a crisis, rapid withdrawal and a subsequent liquidity risk must be expected. As explained in Bernet and Walter (2009), they include savings accounts and short-term deposits by private and business customers and outstanding debts to customers with a short duration (not more than three months).

- **Funding**. Most (16) countries rely on an *ex ante* system in which levies are collected on a regular basis. Six countries collect contributions from banks only if the scheme is triggered (*ex post* systems). The remaining countries adopt a hybrid system combining *ex ante* and *ex post* characteristics.

The Commission's legislative proposal (2010) also focuses attention on the *ex ante* rule, proposing it as the first step in a four-step funding approach.[8]

Furthermore, the contribution paid by each insured institution to the DGS should be related to the risk that the institution itself is taking. In practice, since Directive 94/19/EC has left the decision to the individual countries, not all the MSs adopt a risk-based approach in computing DGS contributions.

- **Co-insurance**. In order to avoid moral hazard, a DGS could lower the level of coverage to 90 %, so that depositors would keep part of the risk in their own hands.

Differences among schemes and the resulting need for more harmonisation, as well as analysis of the performance of DGSs during the current financial crisis, prompted the European Commission to request technical reports[9] (during the period 2006-2009) and to propose a revision of the EU rules (15/10/2008) in order to increase the level of coverage (up to € 100 000 in two steps), abandon the co-insurance mechanism and shorten the payout period. The amendments were adopted by the European Parliament at its plenary meeting and by the Council on 18 December 2008 and 26 February 2009 respectively. The result is Directive 2009/14/EC,[10] which amends Directive 94/19/EC in the direction of further harmonisation.

[8] The four-step funding procedure contained in the Commission proposal is the following: first, *ex ante* financing to constitute a solid reserve. Second, in severe crisis periods, an additional *ex post* contribution is allowed. Third, if the amount is still insufficient, each scheme can borrow a limited amount from other schemes. Fourth, as a last resort, other funding arrangements would be accepted.

[9] Reports are available at http://ec.europa.eu/internal_market/bank/guarantee/index_en.htm#ccr.

[10] Text available at http://ec.europa.eu/internal_market/bank/docs/guarantee/200914_en.pdf.

On 12 July 2010 the Commission proposed additional amendments to Directives 94/19/EC and 2009/94/EC.[11] The key elements of the proposal are the level of coverage (the upgrade to € 100 000 is confirmed), faster payouts, less red tape, better information for bank account holders, long-term and responsible financing reached in a four-step approach that combines solid *ex ante* financing with additional *ex post* contributions where needed. The proposal is accompanied by an impact assessment that estimates the costs associated with the new proposal. The main expected benefits have to do with increasing depositors' confidence. Banks would obviously incur a reduction of their operating profits and some of them might try to pass those costs on to depositors. The worst overall impact over a ten-year period should not exceed a 0.1 % reduction in interest rates on saving accounts or an increase in bank fees on current accounts by about € 7 per year per account (or € 10-12 in a crisis situation).

Both Directive 2009/14/EC and the subsequent proposal stressed the need for prompt harmonisation among EU countries since the current DGS system is fragmented, with schemes covering different groups of depositors, having different coverage levels and imposing different financial obligations on banks.

The harmonisation process required an accurate evaluation of mechanisms adopted in existing schemes, and the European Commission therefore requested scientific reports on which to base its proposed changes to Directive 94/19/EC. Both Directive 2009/14/EC and the 2010 proposal stress the importance of contributions being computed using a procedure that takes into account the risk profile of member banks. The EC JRC issued two reports on risk-based contributions. First, existing procedures were analysed, and then three models for computing risk-based contributions were proposed.

The EC JRC (2008b) report described detailed characteristics of existing risk-based systems across MSs. Only eight DGSs (Italy, Finland, Sweden, France, two schemes in Germany and two schemes in Portugal) took into account the risk profile of member banks. Hungary and Romania

[11] Stage reached: awaiting first reading by the European Parliament.

used partial risk correction that allowed them to increase the contribution whenever a bank 'fails to comply with the prescribed capital adequacy ratio and/or pays its required contribution or advance contribution more than 30 days late' or if it 'has engaged in risky and unsound policies'. In addition, Poland does not adjust contributions according to risk, but the contribution base includes risk-based variables.[12]

This report was the starting point for the EC JRC 2009 report, where the authors suggested a common risk-based approach that could be implemented by EU DGSs, in line with the harmonisation sought by Directive 2009/14/EC. The report started from current practices in the MSs and proposed three models based, respectively, on a single indicator, on multiple indicators and on default probabilities. The first two models are similar to what happens in risk-based corrections currently adopted in MSs, but they are not obtained after an investigation of the reliability of such existing procedures.

The effectiveness of existing schemes is not addressed in the two reports presented above, even though a detailed analysis of how the procedures adopted have been devised would be useful with a view to designing harmonised DGSs across the EU.

The only assessment of schemes' effectiveness is provided by the EC JRC in 'Investigating the efficiency of EU Deposit Guarantee Schemes' (2008a). The report investigates the efficiency of DGSs in terms of their ability to handle reimbursements or prevent interventions. Heterogeneity across MSs does not allow a uniform conclusion to be drawn in terms of intervention procedures. The report also performs a scenario analysis aimed at exploring the capacity of EU DGSs to cope with reimbursements of depositors and preventive interventions of various sizes. The costs associated with each scenario are estimated and then compared to the maximum amount of available money. Again, significant differences emerge among MSs.

[12] For example risk-weighted total balance-sheet assets, guarantees and endorsements and the remaining risk-weighted off-balance sheet liabilities.

The report makes a comparison between various schemes and it notices that some characteristics (for example the *ex ante* mechanism) emerge as the most efficient ones. But it doesn't look inside the individual MS's schemes and their machinery in order to find parts that are working and parts whose functioning could be improved.

This chapter focuses on the Italian DGS with the aim of examining how it operates and how it has performed over the past years. In particular, it analyses the Italian banking system in the light of the rules laid down by the Italian DGS during the period 2006-2010. I found that two out of four indicators were somewhat lacking in explanatory power: starting from this weakness of the Italian method, I propose an alternative methodology for computing risk-based contributions that looks at data about CDS spreads in order to find the best aggregation of the balance sheet indicators employed. With this model I am seeking to suggest a way of monitoring banks' riskiness that combines both consolidated practices developed within DGSs (choices of risk indicators) and the market's view of banking risks (the CDS market). This model is closely related to Chiaramonte and Casu (2010), who confirm the close relationship between CDS spread and certain balance sheet indicators of the banking sector.

1.1.3 The Italian DGS*: Fondo Interbancario di Tutela dei Depositi*

The Italian *Fondo Interbancario di Tutela dei Depositi* (FITD) was established in 1987 on a voluntary membership basis as a private-law mandatory consortium, recognised by the Bank of Italy. Its activities are regulated by its Statutes and by Laws.

Directive 94/19/EC on deposit-guarantee schemes was transposed into Italian law by Legislative Decree 659/96 (which was published in the Official Gazette of the Italian Republic on 27 December 1996 and entered into force on 11 January 1997). As a result, membership of a DGS became mandatory for all Italian banks and the level of coverage was set at €103 291.38 (the equivalent of the original limit of 200 million lire). This level of coverage has now been reduced to € 100 000 as a consequence of Directive 2009/14/EC recently implemented in Italy (D. Lgs. 24 March 2011, in force as of 7/5/2011).

All the FITD's member banks (291 as of 30 June 2010) subscribe to the Fund. Credit cooperative banks, however, join the other mandatory DGS established in Italy, the 'Deposit Guarantee Fund for Cooperative Banks'. This latter, along with the 'Bond Holders Guarantee Fund for Cooperative Credit Banks' (voluntary scheme for credit cooperative banks only) and the 'National Guarantee Fund' (for investors) are the other guarantee schemes active in the Italian safety net.

The FITD's mandate is to protect depositors of member banks. The financial resources for the pursuit of this aim are provided by the consortium members in case of need, i.e. on an *ex post* basis.

In accordance with its Statutes, the Fund can intervene in favour of banks placed in compulsory administrative liquidation,[13] either reimbursing depositors or participating in a transfer of assets and liabilities to an acquiring bank (Articles 27-28). The FITD can also perform support interventions (pursuant to Article 29) in favour of member banks in special administration. The choice between the different types of intervention is made applying the least cost principle. Any intervention by the Fund is subject to the authorisation of the Bank of Italy.

Since the Fund was established in 1987, the contribution system has followed an insurance logic, where member banks are required to pay depending on their level of risk.

To that end, banks are required to send to the Fund data on their contribution base and on balance sheet ratios, according to the statutory reports system provided for in the FITD Statutes. A distinction is drawn among the sources of data used for the statutory reports system: the Fund receives data for the contribution base directly from member banks, while the supervisory authority provides data needed for calculating the balance sheet ratios.

The contribution base is the key variable used for calculating the amount of member banks' contributions both to operating expenses and to interventions (Article 25 of the Statutes). The contribution quota is based on the portion of each bank's deposits covered by the Fund and it is calculated in three steps. First, the proportional quota of the contribution base, expressed in thousandths, is given by the individual contribution base over the total reimbursable funds. Second, the 'regressive correction method' (Article 14 of the Appendix to the Statutes) modifies the proportional quota using an increasing/decreasing percentage inversely linked to the size of the bank, which is expressed by the amount of its contribution base. The increase or reduction in the proportional quota may vary between +7.5 % and –7.5 %. Third, a correction method linked to the bank riskiness in balance sheet ratios is applied; this is based on the value of the 'weighted average aggregate indicator' (WAAI, Article 5 of the Appendix to the Statutes), calculated for each bank as the average of the value of its aggregate indicators (AIs) in the previous three six-monthly reports on balance sheet ratios that the bank has submitted to the Fund. The impact of the WAAI on the regressive quota is +20 % and -20 %.

The Fund evaluates the riskiness of its member banks through a system of four ratios relating to three profiles: risk, solvency, and profitability (Article 6 of the Appendix to the Statutes). Ratios are calculated half-yearly or quarterly, depending on the risk level of the individual member bank.

The ratios are as follows:

Risk profile:

A1 = bad loans/supervisory capital

Solvency profile:

[13] Compulsory administrative liquidation and special administration are the special bankruptcy regimes for banks provided for by the Italian banking law.

B1 = supervisory capital, including Tier 3/supervisory capital requirements

Profitability profile:

D1 = operating expenses/gross income (cost to income ratio)

D2 = loan losses, net of recoveries/profit before tax

Three thresholds are set for each ratio (Table 1.4) using the ‘method of percentiles’, which consists in dividing at 75%, 85% and 95% the distribution of each indicator. Appling this method, the ratios are divided into four classes, called ‘Normal’, ‘Attention’, ‘Warning’ and ‘Violation’, in which member banks are rated.

Table 1.4: Ratios and thresholds

Ratios	Risk classes			
	Normal	**Attention**	**Warning**	**Violation**
A1: bad loans/supervisory capital	*<=20%* (Coeff 0)	*(20%;30%]* (Coeff 2)	*(30%;50%]* (Coeff 4)	*> 50%* (Coeff 8)
B1: supervisory capital, incl. Tier 3/supervisory capital requirements	*>110%* (Coeff 0)	*(100%;110%]* (Coeff 1)	*(90%;100%]* (Coeff 2)	*<= 90%* (Coeff 4)
D1: operating expenses/ gross income	*<= 70%* (Coeff 0)	*(70%;80%]* (Coeff 1)	*(80%;90%]* (Coeff 2)	*> 90% or D1<0* (Coeff 4)
D2: loan losses/profit before tax	*<= 40% or num <0* (Coeff 0)	*(40%;50%]* (Coeff 1)	*(50%;60%]* (Coeff 2)	*>60% or den < 0* (Coeff 4)

The sum of the coefficients of each ratio determines the aggregate indicator (AI), which can vary from 0 up to 20. According to the value of the AI, the bank is assigned a rating class defined as its ‘statutory position’ (Table 1.5).

Table 1.5: AI and statutory positions

- **A)** AI from 0 to 3, the bank is in ***Normal***
- **B)** AI from 4 to 5, the bank is in ***Attention***
- **C)** AI from 6 to 7, the bank is in ***Warning***
- **D)** AI from 8 to 10, the bank is in ***Penalty***
- **E)** AI from 11 to 12, the bank is in ***Severe imbalance***
- **F)** AI from 13 to 20, the bank is in ***Expulsion***

Banks rated in the first two statutory positions (Normal and Attention) are considered at ‘low risk’; banks in Warning and Penalty are at ‘medium risk’, while banks in Severe imbalance and in the Expulsion class are at ‘high risk’.

The characteristics of the Italian DGS are summarised in the table below.

***Table 1.6**: Characteristics of the Italian system*

	Description
Fund mechanism	*Ex post*
Fund’s finance	*Ex post* + small annual contribution to cover administrative expenses
Risk-based contributions	Contributions are corrected using a risk-based method based on a composite indicator
Competent authority	FITD (interventions are authorised by the Bank of Italy)
Trigger event	Declaration of unavailability of deposits
Types of intervention	- Banks in compulsory administrative liquidation: reimbursement of depositors or transfer of assets and liabilities to an acquiring bank - Banks in special administration: support interventions

Reimbursement	Seven business days

1.1.4 Credit default swaps (CDSs): definitions and literature review

A CDS is a type of credit derivative designed to isolate the risk of default on credit obligations.

Credit derivatives are in general conceived to hedge, transfer, or manage credit risk and therefore they can be thought of as insurance against default. Two counterparties are involved, the protection buyer and the protection seller. The insured event is the loss arising from a default, the premium paid is the fee, and the maximum covered loss is called the notional amount (see Stulz, 2009). As explained in Cariboni et al. (2009), the idea is that credit risk is transferred without reallocating the ownership of the underlying asset.

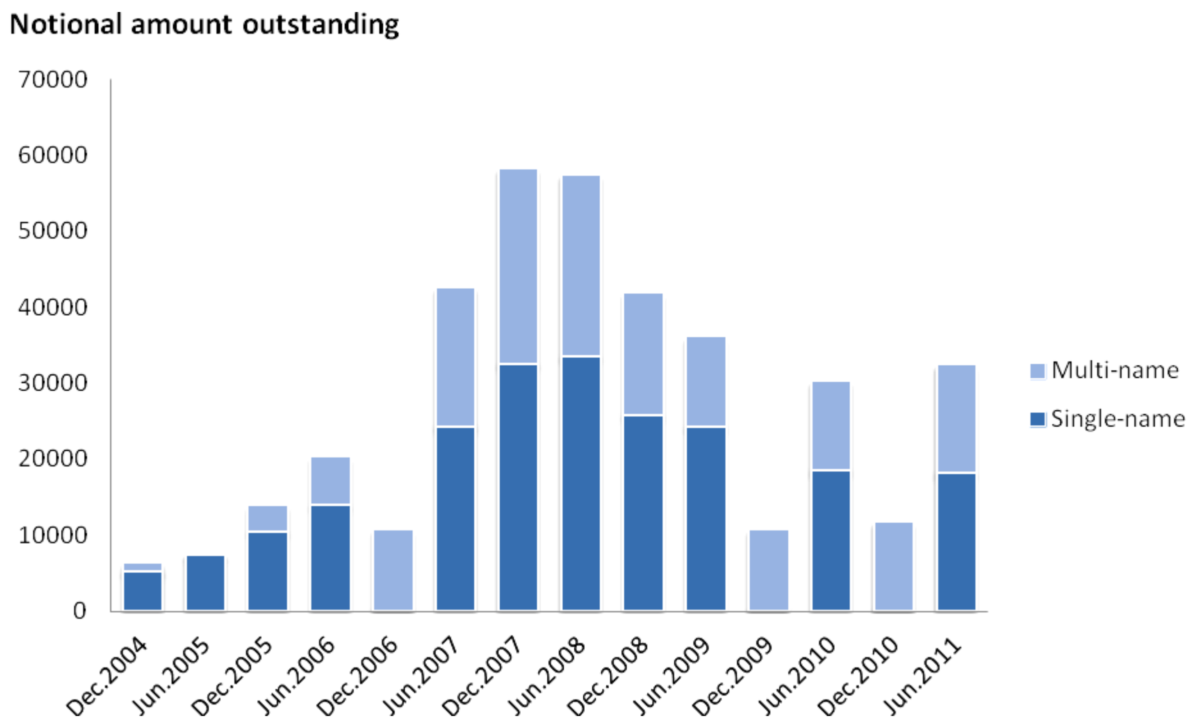
CDSs take up a very large share of the credit derivatives market. They trade over the counter on a dealers' market where dealers trade with end-users as well as with other dealers. A CDS is a bilateral agreement whereby the protection buyer transfers the credit risk of a reference entity to the protection seller for a specified length of time. The buyer of the protection makes predetermined payments to the seller until either the maturity date is reached or the default event occurs. In the latter case, the protection buyer pays the protection seller a specified amount. The CDS spread is the yearly rate paid by the protection buyer to enter the contract against the default of the reference entity. Thus, it reflects the riskiness of the underlying credit.

Since CDSs are traded over the counter and they are not regulated, an official record of contracts does not exist. The Bank for International Settlements (BIS) has survey data on CDSs starting from the end of 2004:[14] at that time the total notional amount was \$6 trillion (80% of which represented by single-name contracts). At the end of June 2008 the size of the market was \$57 trillion, and in the second half of 2008 the market fell sharply to \$41 trillion (single-name contracts represented 58% of the market). The downward trend continued in the next two years:

[14] http://www.bis.org/statistics/otcder/dt1920a.pdf.

at the end of 2009 the notional amount outstanding was $ 33 trillion and in December 2010 it was $ 30 trillion. In the first half of 2011 the size of the market increased, to $ 32 trillion in June 2011.

Figure 1.3: *Credit default swaps, notional amount outstanding 2004-2011 (in billion US dollars)*



Source: BIS (2011 Q2)

Literature on CDSs started to grow from 2004, when the size of the CDS market became significantly large. It is divided into two strands: papers dedicated to the pricing characteristics of CDS spreads and papers focusing on the determinants of CDS spreads.

In the first group there are empirical analyses investigating the ability of CDS spreads to incorporate firm-specific information. Some empirical studies (see for example Blanco et al.,

2005) prove the superiority of CDS spreads over corporate bond spreads in terms of price discovery: it has been shown that information mostly flows from CDS prices to bond prices.

Models for determinants of credit spread risk are usually classified into two categories: structural models and reduced form models.[15]

Structural models originate from the option pricing model developed by Black and Scholes (1973): they view bonds subject to credit risk as options written on the value of an underlying firm's assets. In this case default occurs when the market value of those assets reaches specified thresholds. The first author developing structural models on credit risk was Merton (1974); since then a number of generalised models have been proposed.

Reduced form models use only market-determined prices or parameters that can be estimated, as explained by Skinner and Diaz (2003). They treat defaults as exogenous events modelled and calibrated using market data.

Before the surge of the CDS market, empirical studies looking for the determinants of credit risk were based only on corporate spreads. Elton et al. (2001), Driessen (2005) and Amato and Remolona (2005) focus on the 'credit spread puzzle', trying to explain why historical default losses are not aligned with observed credit premia. A second group of empirical studies tries to identify determinants of credit spreads in a statistical way by regressing observed spreads on factors identified by theoretical models as explanatory variables (see for example Collin-Dufresne et al., 2001; Campbell and Taksler, 2003; Guazzarotti, 2004; Avramov et al., 2007; Cremers et al., 2004).

The first papers focusing on the determinants of CDS spreads suggest that, in addition to credit risk, CDS spreads reflect some other factors. For example, Aunon-Nerin et al. (2002) focus on contracts that were traded between January 1998 and February 2000 (with both sovereign and corporate underlying assets) to investigate the influence of some fundamental variables on a

[15] Detailed references on reduced form models and structural models can be found in Jarrow and Protter (2004).

cross-section of credit default transaction data. They find that ratings, asset volatility, the size and direction of stock price changes and leverage together with market information are able to explain up to 82% of the variation in CDS pricing. Zhang et al. (2005) focus on five-year CDS contracts written on US entities (sovereign excluded) during the period January 2001 – December 2003. The authors explain the time series and cross-sectional variation in CDS spreads using a decomposition of realized equity volatility into a permanent part plus individual equity jumps (identified using high-frequency data). Combining equity volatility and jump risks and controlling for credit ratings, macroeconomic variables and balance sheet information, they are able to explain up to 75% of CDS spreads. Ericsson et al. (2009) investigate the relationship between theoretical determinants of default risk and actual market premia using linear regressions on a sample of CDS on senior debt in the period 1999 – 2002. They find that firm leverage, volatility and the risk-free interest rate have a significant effect on default risk. Di Cesare and Guazzarotti (2009) focus on a sample of US non-financial firms over the period January 2002 – March 2009 in order to identify determinants of CDS spreads. Their results confirm that factors[16] predicted by the theory as being relevant for CDSs have good explanatory power. Results remain valid also dividing the analysis into periods before the crisis (January 2002 – June 2007) and during the crisis (July 2007 – March 2009).

More recent papers consider only bank CDS spreads in order to test whether those factors that determine CDS spread in non-financial institutions remain valid also for the banking sector.

Almer et al. (2008) work on daily EUR-denominated CDS quotes relating to financial institutions during the period January 2001 – December 2007. Firstly, they show that short-term (six-month) and long-term (five-year) spreads have a high correlation during the whole period. Dividing the analysis into sub-periods, they find that in periods of turbulence spreads have the tendency to co-move; in calm markets they seem independent. They also seek to identify factors that drive short-

[16] Equity volatility, leverage, interest rates (five-year zero-coupon rate on US government bonds), (log) returns of the firms' stocks, the slope of the yield curve, an equity market index, an index of market uncertainty, an index of the

and/or long-term CDS spreads. They find that five-year spreads are significantly sensitive to asset volatility, stock process and interest rate levels. Moreover, five-year spreads are not sensitive to liquidity factors and six-month spreads are sensitive neither to insolvency nor to illiquidity factors. In particular, none of the factors tested seem to significantly explain short-term spreads.

Annaert et al. (2009) perform an empirical analysis of the determinants of CDS spread changes for 31 listed Euro-area banks over the period January 2004 – October 2008. They find three main results: first, the determinants of changes in bank CDS spreads exhibit significant time variation. Second, variables suggested by structural credit risk models (risk-free interest rate, leverage and asset volatility) are not significant in explaining bank CDS spread changes, both in the period prior to the crisis and in the crisis period itself. However, some of the variables proxying for business conditions, market conditions and uncertainty[17] are significant, but both the magnitude and the sign of coefficients have changed over time. Third, CDS market liquidity became a significant factor in explaining bank CDS spread changes when the crisis broke out in the summer of 2007.

Chiaramonte and Casu (2010) investigate the relationship between balance sheet ratios and CDS spreads in three periods: pre-crisis (January 2005 – June 2007), crisis (July 2007 – March 2009) and during-and-post-crisis (April 2009 – March 2010). This is the first paper that uses specifically balance sheet information to explain variations in CDS spreads. More particularly, they analyse the following explanatory variables:

- Asset quality: loan loss reserve/gross loan and unreserved impairment loans/equity;
- Capital: Tier 1 ratio and equity/total assets (leverage);
- Operations: return on average assets (ROA) and return on average equity (ROE);

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premium required by investors to hold riskier assets and the theoretical CDS spread computed using the Merton model.

[17] Slope of the term structure, swap spreads and corporate bond spreads, stock market returns and stock market volatility.

- Liquidity: net loans/(deposits + short-term funding) and liquid assets/(deposits + short-term funding).

Their sample is composed of 57 international banks (43 of which are European). They find that both in the pre-crisis and — in particular — in the crisis periods bank CDS spreads reflect the risk captured by balance sheet ratios. But significant explanatory variables are different in the three sub-periods considered. In particular, the ratio of loan loss reserve to gross loans is the only significant variable in all three periods. Both leverage and the Tier 1 ratio are never among the determinants of CDS spreads and, finally, liquidity does not explain CDS spreads in the pre-crisis period.

Some other papers focusing on the banking sector analyze CDS spreads in order to explain details of the current financial crisis. Eichengreen et al. (2009) investigate common components driving the variance of CDS spreads before and during the crisis. They focus on CDS spreads of the 45 largest financial institutions in the US, the UK, Germany, Switzerland, France, Italy, the Netherlands, Spain and Portugal. They use principal components analysis to extract the common factors in weekly variations in the CDS spreads of individual banks. Their results show that the share of common factors (associated with US high-yield spreads) was already quite high prior to June 2007. The share rose in the period between June 2007 and September 2008 (Lehman's failure) and in the same period the association between common factors and US high-yield spreads declined, while the association with measures of banks' own credit risk and of generalised risk aversion increased. After September 2008, there was a further brief increase in the share of the variance accounted for by common components, but then, even if the level of CDS spreads remained high, the share of the variance accounted for by the common factors decreased significantly. In this period common components seem again related to US high-yield spreads as well as to measures of funding and credit risk.

Calice and Ioannidis (2009) focus on the group of large complex financial institutions (LCFIs) as defined by the Bank of England (2001). They investigate the dynamics between banks' equity returns and major tranched CDS indices using a VAR model. In particular, they use the five-year North American CDX and the equivalent European series, namely the five-year main iTraxx Europe. They find that CDS indices in Europe and the US are important in explaining the movement in LCFIs' equity prices, as are credit fundamentals. Additionally, they find robust short-run evidence of an overall increase in correlations across these two markets since the middle of 2007.

Huang et al. (2008) propose a framework for measuring and stress-testing the systemic risk of a group of major financial institutions. CDS spreads are used together with equity prices of individual banks in order to construct an indicator of systemic risk in the banking sector. In particular, single-name CDS spreads are used to derive probabilities of default associated with a sample composed of 12 major US banks during the period 2001-2008. The peak of their systemic risk indicator aligns well with periods of major adverse developments in the market.

Hart and Zingales (2009) use CDS spreads to design a new capital requirement for large financial institutions (LFIs) that are too big to fail. Since the CDS indicates the risk that the LFI will fail, the authors suggest that whenever the CDS price rises above a critical threshold, the regulator should force the LFI to issue equity until the CDS price moves back below the threshold. If this does not happen within a predetermined period of time, the regulator should intervene.

Volz and Wedow (2009) analyse the potential distortion of prices in the CDS market caused by the too-big-to-fail issue. In particular, they examine the information content of CDS spreads for a sample of 91 banks from 24 countries. Overall, they find that CDS spreads reflect banks' risk. However, they further detect an important size effect that vindicates the existence of a distortion due to the too-big-to-fail issue.

Raunig and Scheicher (2009) analyse how investors in the corporate debt market view banks using monthly data on CDS spreads of 41 major banks and 162 non-banks. They compare the market pricing of banks to industrial firms and by means of CDS spreads they study whether investors discriminate between the riskiness of banks and other types of firms by requiring different risk premia or by modifying their expected loss measures. Their analysis indicates that until July 2007 bank debt was perceived as being less risky than non-bank debt. However, after the outbreak of the financial market turmoil, the market perceptions of bank and non-bank credit risk reached similar levels.

The present contribution starts from the paper by Chiaramonte and Casu (2010), which provides evidence of the close relationship between CDS spreads and information contained in banks' balance sheets. Their work, together with preceding contributions focusing on determinants of CDS spreads, highlights the fact that CDS spreads represent not only credit risk, but the more general state of health of the financial institutions concerned.

In this chapter the set of balance sheet ratios used is composed of the four indicators used in the Italian DGS to compute risk-based contributions. Regarding CDS spreads, five-year spreads for 48 European banking groups are considered. The relationship between CDSs and balance sheets is investigated through linear regressions using as explanatory variables ratios computed for the 48 banks during the period 2006-2010. The regression coefficients are then used with the sample of Italian banks in order to compute an indicator of bank riskiness whose performance is compared with that of the FITD aggregate indicator.

This work is also linked to the strand of literature that focuses on the current financial crisis: it examines how results changed during the period 2006-2010 in order to highlight any differences in the relationship between CDS and balance sheet ratios arising during the crisis periods.

Results show that balance sheet ratios are able to explain a large portion of CDS spreads, although some ratios seem more significant than others. Thus, in principle it is possible to use CDS spreads to calibrate methodologies currently used in EU DGS.

1.2 Methodology

The methodology employed in this chapter consists in four steps:

- Investigation of the explanatory power of procedures currently applied at the FITD for the computation of risk-based contributions;
- Investigation of the relationship between CDS spreads and balance sheet ratios used at the FITD in a sample composed of 48 European banks issuing CDSs;
- Construction of an alternative indicator of (Italian) bank riskiness using regression coefficients found in the previous step;
- Comparison of the performance of the new indicators with the current indicator applied at the Italian DGS.

The Italian CAMEL model used at the FITD develops a composite indicator (the aggregate indicator) using an aggregation of the four individual ratios (A1, B1, D1, D2) presented in section 1.1.3. The mathematical model underlying the indicator is made of all choices applied to the individual variables aggregated. The FITD currently composes the aggregate indicator (AI) using an arithmetic average of the variables involved: it is derived from

$$AI_j = \sum_{i=1}^{k} \omega_i x_{ji} \quad ,$$

where

- $j=1,\dots,J$ is the individual bank being measured by the composite indicator,
- J is the number of banks involved,
- $x_{j1},\dots x_{jk}$ are the coefficients associated with bank j over the k ratios X_i,
- ω_i is the weight associated with X_i.

In the specific case of the FITD, the weights associated with the coefficients for the ratios imply a difference between A1, which is assigned double importance, and the other three ratios, which are equally weighted.

The design of composite indicators involves making assumptions about the relative importance of their components. Looking at the Italian situation, the choice of weights ω_i is equivalent to assigning relative importance to the individual components of the aggregate index.

As a **first step**, the explanatory power of the Italian model is investigated by looking at its performance during the period 2006-2010: details are therefore provided about the discriminatory power of the four individual ratios during the years considered. The construction of the aggregate indicator is also investigated using sensitivity analysis (SA) tools.

SA can be employed to explore the relationship between the inputs and the output of the model analyzed. In this specific situation, SA is a way of investigating the relationship between balance sheet ratios and the aggregate indicator. Here I test the importance of the variables using a variance-based measure S_i commonly used by practitioners of sensitivity analysis (Saltelli and Tarantola, 2002). This measure is known under different names in different communities, as a measure of importance, Pearson's correlation ratio or a first-order sensitivity index. S_i is defined as follows:

$$S_i = \frac{V_{X_i}(E_{X-i}(Y|X_i))}{V(Y)} \quad (1)$$

S_i is based on global sensitivity analysis theory, where these concepts are ordinarily traded. One might ask the question 'What happens to the variance of Y if one variable is fixed?' The point is that we do not know where to fix a variable, and furthermore we would like to get rid of the dependency on the fixing point. To do this the question could be rephrased as follows: 'What is the reduction in the variance of Y that we would get on average by fixing a variable to all its possible values?'

It is evident that the reduced variance obtained on average by fixing a variable can be written as:

$$E_{X_i}(V_{X-i}(Y|X_i))$$

Due to the known identity

$$V_{X_i}(E_{X-i}(Y|X_i)) + E_{X_i}(V_{X-i}(Y|X_i)) = V(Y)$$

then we can call $V_{X_i}(E_{X-i}(Y|X_i))$ the reduction in variance of the composite indicator to be expected by fixing a variable. Note that so far we have not assumed that variables are independent. In sensitivity analysis one uses — also for the case of correlated variables — a first-order sensitivity measure (also termed main effect) that is defined as the ratio between $V_{X_i}(E_{X-i}(Y|X_i))$ and the unconditional variance, as expressed in the above formula.

The main difference between the uncorrelated and the correlated case is that in the former the sum of the S_i must be less than or equal to one (with $\sum S_i = 1$ when no interactions exist between variables), while for the correlated variables this sum might well exceed one.

In order to compute S_i we can make use of the following equation:

$$V_{X_i}(E_{X-i}(Y|X_i)) = V(f_i(X_i))$$ [18]

The equation above says that all that is needed to compute $V_{X_i}(E_{X-i}(Y|X_i))$ is a good estimate of function *f(i)*. This latter can be derived by an appropriate interpolation and smoothing algorithm applied to a simple scatter plot of the composite indicator Y's scores *versus* any variable X_i.

Following Ratto and Pagano (2010), the values of S_i can be estimated using a non-parametric multivariate smoothing approach called state-dependent regression that is equivalent to smoothing splines and kernel regression but is performed using a recursive algorithm to identify relevant ANOVA terms.[19] In the simple case where *f(i)* is a linear function, S_i reduces to R_i^2 the square of Pearson's correlation between Y and X_i. Note that this smoothing approach is but one of many possible strategies to estimate the values of S_i. In Paruolo et al. (2011), kernel regression is used, while in many modelling applications design points are used (see Saltelli et al., 2010 for a review).

The main effect S_i is an appealing measure of importance of a variable for several reasons (Paruolo et al., 2011):

- it offers a precise definition of importance, namely 'the expected reduction in variance of the composite indicator that would be obtained if a variable could be fixed';
- it is always positive, which makes it interpretable in all cases;
- it can be used regardless of the degree of correlation between variables;

[18] See Paruolo et al. (2011).
[19] See Ratto and Pagano (2010).

- it is ‘model-free’, which means that it can be applied in principle also in non-linear aggregations, unlike the effective weights or the Pearson correlation coefficient that are constrained by the linear assumption; and finally
- it is not invasive, which means that no changes are made to the composite indicator or to the correlation structure of the indicators. This is contrasted with the technique of eliminating one indicator at a time in order to assess its impact on the final ranking.

Sensitivity analysis and analysis of the performance of the individual ratios over the period 2006-2010 will reveal poor informative power particularly associated with indicator B1.

Given the previous analysis, a — partial — revision of the Italian methodology should be envisaged. Several methods could be employed to modify the current way of evaluating riskiness in the banking system. For example, thresholds associated with individual indicators could be modified in order to obtain more informative power and better sensitivity indices. However, I decided to explore the connection between ratios used at the FITD and the market value of default risk expressed by CDS spreads.

Thus, as a **second step**, the relationship between five-year CDS spreads for 48 European banks and FITD balance sheet ratios constructed for the same sample of banks was investigated. A panel data regression was used as follows:

$$CDS_{jt} = \beta x_{jt} + \varepsilon_{jt}$$

Where *j* represents the individual bank, and *t* indicates the time periods. The explanatory variables involved are the four bank balance sheet ratios used at the FITD: A1, B1, D1, D2.

Regressions are conducted firstly on the whole of the period considered, 2006-2010, and then over the core crisis period 2008-2010. This is in line with Laeven and Valencia (2010), who identify the starting year of the banking crisis as 2008 for non-US and non-UK countries. Since only annual balance sheet data are available the sample period cannot be divided into three sub-periods as Chiaramonte and Casu (2010) do in their paper. As explained in Chiaramonte and Casu (2010), bank CDS spreads do not react in advance to the crisis and require less than a three-month lag to incorporate the balance sheet information. Thus, it can be considered correct to run regressions with both bank CDS spreads and balance sheet variables at time *t*.

As a **third step**, the beta coefficients found in the panel regressions performed in the previous step were kept and an indicator of bank riskiness was constructed that represents an alternative to the one used in the Italian framework.

The **last step** consisted in comparing the performance of the current Italian model with the performance associated with the new indicator constructed using CDS spreads. The comparison reveals a common trend in the two indicators during the period 2006-2010.

1.3 Data sample and descriptive statistics

1.3.1 Bank CDS spreads

European banking groups associated with five-year CDS spreads were considered. The limited number of banks contained in the sample (48) derives from the decision to focus on the banking sector within EU countries.

The analysis is divided into two periods: 2006-2010 and 2008-2010. Daily spreads were available from January 2006 to December 2010 for the 48 banks. The average spread over the last 15 days[20] of December of each year considered was taken since only annual data were available for balance sheet variables.

Data were extracted from Bloomberg, accessed using Bocconi University electronic resources.

[20] Taking the average over the entire month does not produce different results.

Descriptive statistics of CDS spreads for 48 European banks in 2006-2010 and in 2008-2010 are presented in the table below:

Table 1.7: *CDS spreads, summary statistics*

	2006-2010			2008-2010		
	Mean	**Min**	**Max**	**Mean**	**Min**	**Max**
AT	0.023	0.002	0.042	0.014	0.005	0.031
BE	0.031	0.010	0.049	0.018	0.007	0.049
DE	0.016	0.001	0.069	**0.018**	0.000	0.069
DK	0.012	0.001	0.023	0.011	0.005	0.019
ES	0.021	0.001	0.068	**0.030**	0.012	0.068
FR	0.017	0.001	0.042	**0.021**	0.014	0.029
GB	0.013	0.001	0.029	**0.023**	0.000	0.046
GR	0.093	0.041	0.145	0.081	0.017	0.145
IE	0.076	0.001	0.424	**0.098**	0.013	0.424
IT	0.021	0.000	0.191	0.018	0.000	0.132
NL	0.035	0.001	0.286	0.024	0.000	0.045
PT	0.035	0.001	0.132	**0.054**	0.010	0.132
SE	0.010	0.002	0.020	**0.034**	0.009	0.073
Entire sample	0.027	0.000	0.424	0.030	0.000	0.424

Notes: AT=Austria, BE=Belgium, DE=Germany, DK=Denmark, ES=Spain, FR=France, GB=UK, GR=Greece, IE=Ireland, IT=Italy, NL=The Netherlands, PT=Portugal, SE=Sweden.

As can be seen from the table above, there is a slight increase in the average CDS spread in the last three available years. Countries that experienced such an increase are highlighted in light blue.

The following average annual CDS spreads were obtained per country:

Table 1.8: *Annual average CDS spread per country*

	2006	**2007**	**2008**	**2009**	**2010**
AT	0.0018	0.0077	0.0360	0.0232	0.0286

BE	na	na	0.0463	0.0207	0.0346
DE	0.0020	0.0090	0.0166	0.0163	0.0335
DK	0.0008	0.0054	0.0229	0.0129	0.0191
ES	0.0017	0.0090	0.0262	0.0175	0.0494
FR	0.0010	0.0070	0.0272	0.0160	0.0237
GB	0.0009	0.0075	0.0218	0.0121	0.0205
GR	na	na	na	0.0409	0.1451
IE	0.0011	0.0149	0.0427	0.0529	0.2414
IT	0.0010	0.0065	0.0413	0.0122	0.0276
NL	0.0010	0.0067	0.0999	0.0229	0.0280
PT	0.0015	0.0080	0.0170	0.0169	0.1312
SE	0.0021	0.0022	0.0187	0.0097	0.0112
Average	**0.0014**	**0.0082**	**0.0387**	**0.0198**	**0.0529**

Spreads range from a minimum value of 0.0014 in 2006 to a maximum of 0.0387 in 2008. Countries are not homogeneous. The highest values are associated with Greece (only two years of available data), which reaches 0.1451 in 2010.

1.3.2 Balance sheet ratios

The Italian DGS employs four ratios representing three bank profiles: risk, solvency and profitability. For this reason it can be regarded as a CAMEL system without liquidity and management profiles. The three risk profiles are investigated as follows:

Risk profile

The risk profile is represented by A1, constructed as bad loans/supervisory capital. A1 is easily interpretable as the ratio focused on credit risk: it highlights the risk that a bank is suffering losses that could cause it to fail. In this sense, it can be defined as the capacity of the bank to face losses (impaired loans) without becoming insolvent. A high A1 implies high risk because the magnitude of bad loans is not supported by the total amount of capital required by the Basel regulation. In the analysis involving CDS spreads I expect a positive relationship between A1 and CDS spreads.

Solvency profile

B1 is constructed as the ratio supervisory capital (including Tier 3)/supervisory capital requirements and it represents the capital adequacy of a bank. The numerator is the total capital requirement, whereas the denominator represents 8 % of risk-weighted assets. That is why a high B1 implies better capitalisation. I thus expect a negative relationship between B1 and CDS spreads.

Profitability profile

Profitability is analyzed through two indicators constructed using variables taken from the income statement.

- D1 is the ratio operating expenses/gross income (cost to income ratio). It represents the ordinary activity of the bank and it shows its ability to cover operating costs. A high D1 or a negative D1 represent a high-risk situation. The non-monotonic behaviour of D1 will be taken into account in the section involving CDS spreads. In fact, in the samples considered here there are no negative values for D1. This leaves an indicator that should exhibit a positive relationship with CDS spreads.
- D2 is loan losses (net of recoveries)/profit before tax. It represents the efficiency of the bank in managing its ordinary activity. The numerator is composed of loan loss provisions plus loan loss reserves. Looking at this ratio, risk is gathered by either a high positive D2 or by a negative D2 caused by a negative denominator. The non-monotonic behaviour of D2 will be taken into account in the section involving CDS spreads.

The four ratios were constructed for the period 2006-2010 for the set of Italian banks derived from the FITD and for the set of 48 EU banks issuing CDSs. Data for the second group are only available on an annual basis, so the entire analysis is conducted using annual data. The following paragraphs describe balance sheet ratios computed for the two samples as well as the composition of both bank groups.

Data about Italian banks are provided by the FITD. Usually the FITD receives data on a half-yearly basis from the 'Matrix of the Central Bank of Italy'. Annual data are used for the period 2006-2009, whereas balance sheet information related to 2010 is provided by the (publicly available) ABI dataset.

The introduction of International Accounting Standards at the end of 2005 forces us to use data starting from January 2006 in order to have fully comparable balance sheet extractions.

The analysis involves all the FITD's member banks (around 300), which represent over 90 % of total eligible deposits as of June 2010 (693.5 billion €). This means that the dataset draws a complete picture of the Italian banking system. More specifically, the dataset contains 263 banks in 2006, 265 in 2007, 252 in 2008, 240 in 2009 and 208 in 2010. The original dataset was reduced by eliminating banks that benefit from exceptions. As explained earlier, according to the value taken by ratios each bank is located in a specific risk class. This is not valid for three categories of banks: start-up banks, non-EU banks from G10 countries and banks with no reimbursable funds. The first category benefits from a reduction of the coefficient assigned to indicators D1 and D2; the second one has a similar reduction applied to B1. For the third category the coefficient of ratios A1, D1 and D2 is reduced to 0.

Descriptive statistics[21] are provided in Table 1.9, which contains data about the entire period and also about the central crisis period.

Table 1.9: *Descriptive statistics. FITD sample, 2006-2010*

	2006-2010			2008-2010		
	Mean	**Min**	**Max**	**Mean**	**Min**	**Max**

[21] Data about balance sheet ratios are always expressed as %.

A1	10.65	-4.48	136.48	12.89	0.00	136.48
B1	277.34	-70.25	5 968.14	269.26	-18.59	2 990.17
D1	71.66	-819.34	1 808.56	78.50	-819.34	1 808.56
D2	-17.77	-37 900.00	4 582.15	-35.59	-37 900.00	4 582.15

As can be seen from the table above, there is no significant change if we consider the central part of the crisis period. The negative average value of D2 is driven by extreme negative values in the sample. As explained earlier, this means high risk only if the negative sign is due to a negative denominator.

Looking at annual average values (Table 1.10), we notice a deterioration of ratios. In particular, A1 increases, B1 drops starting from 2007 and D1 increases until 2009. D2 doesn't show a clear tendency because of the large variability in D2 data. For this reason a winsoring procedure was applied such that extreme values at both the left and the right extremes of the distributions were replaced by the first available value considered as 'not extreme'. After this modification, D2 shows an increasing trend until 2009, which is consistent with the higher riskiness showed by the other indicators.

Table 1.10: *Annual average values, FITD sample*

	2006	**2007**	**2008**	**2009**	**2010**
A1	7.57	7.77	9.19	12.82	17.47
B1	271.13	304.84	285.60	266.67	252.45
D1	62.00	63.17	72.87	82.70	80.47
D2	-1.38	13.01	-0.41	67.20	-196.80

Table 1.11: *D2, annual average values. FITD sample modified using winsoring procedure (for values above the 0.975 and below the 0.025 percentiles)*

	2006	**2007**	**2008**	**2009**	**2010**
D2	14.82	15.54	24.96	40.23	35.17

The next table provides details about correlations between indicators in the FITD sample. Correlation coefficients are computed both for 2006-2010 and for 2008-2010.

Table 1.12: *Correlation coefficients between balance sheet ratios, FITD sample*

	2006-2010				2008-2010			
	A1	**B1**	**D1**	**D2**	**A1**	**B1**	**D1**	**D2**
A1	1				1			
B1	-25%	1			-32%	1		
D1	2%	18%	1		-1%	29%	1	
D2	-5%	0%	-2%	1	-6%	0%	-3%	1

The four ratios are slightly correlated to each other, confirming that indicators are capturing different risk profiles, and their aggregation could offer a spread picture of banks' exposures. The largest data are represented by the correlations between B1 and A1 (-25%) and between B1 and D1 (18%). Such behaviour is confirmed if we look specifically at the central crisis period.

Larger values are obtained considering D2 without extreme values:

Table 1.13: *Correlation coefficients with D2 modified (winsoring), FITD sample*

	2006-2010				2008-2010			
	A1	**B1**	**D1**	**D2**	**A1**	**B1**	**D1**	**D2**
D2	23%	-15%	-11%	1	20%	-19%	-13%	1

The second sample of banks is composed of the 48 European banking groups issuing CDSs. The small size of the sample is due to the focus on European banks. As explained in Chiaramonte and Casu (2010), only a limited number of banks are involved in CDS activities, and in credit derivatives in general. The dataset contains 25 banking groups in 2006, 30 in 2007, 33 in 2008, 37 in 2009 and 40 in 2010. They are distributed among European countries as follows:

Table 1.14: *Number of banking groups per country*

Country	AT	BE	DE	DK	ES	FR	GB	GR	IE	IT	NL	PT	SE
Number of banks	3	2	8	1	3	4	7	1	3	8	4	2	2

Balance sheet ratios are computed using Bankscope™, a database provided by Bureau van Dijk Electronic Publishing (BvDEP) that contains balance sheet data for banks worldwide. The table below sets out descriptive statistics about the sample of banks issuing CDSs.

Table 1.15: *Descriptive statistics. Bankscope sample, 2006-2010*

	2006-2010			**2008-2010**		
	Mean	**Min**	**Max**	**Mean**	**Min**	**Max**
A1	42.54	2.39	513.78	53.26	4.65	513.78
B1	155.56	50.90	523.30	164.26	50.90	523.30
D1	65.04	16.64	271.66	67.51	16.64	271.66
D2	353.45	-8271.37	21229.95	399.94	-8271.37	21229.95

Again, the two periods considered do not show significant differences in average values. Nevertheless, comparing Table 1.9 and Table 1.15, the two samples seem quite different, at least in terms of average and min/max. In both samples the analysis of averages over the five years considered confirm the tendency towards a deterioration in balance sheet ratios from 2006 to 2010.

Table 1.16: *Annual average values. Bankscope sample, 2006-2010*

	2006	2007	2008	2009	2010
A1	19.64	22.31	45.22	51.67	61.38
B1	140.45	136.26	140.34	166.55	181.87
D1	58.99	61.03	76.96	61.64	65.16
D2	119.71	377.75	-12.66	858.51	316.15

Table 1.17: *D2, annual average values. Bankscope sample modified using winsoring procedure (for values above the 0.975 and below the 0.025 percentiles), 2006-2010*

	2006	2007	2008	2009	2010
D2	119.71	272.50	238.23	333.76	317.83

A1 rises in the period under consideration, B1 decreases in 2007 and then it increases in the following years, D1 decreases until 2008 and then increases in 2009 and 2010. Its behaviour is similar to the dynamic of the D1 associated with the other sample except for the pattern in 2006-2007. D2, after winsoring, rises until 2009, as in the FITD sample.

Balance sheet ratios are correlated in the following way:

Table 1.18: *Correlation coefficients between balance sheet ratios. Bankscope sample, 2006-2010*

	2006-2010				2008-2010			
	A1	**B1**	**D1**	**D2**	**A1**	**B1**	**D1**	**D2**
A1	1				1			
B1	-4%	1			-12%	1		
D1	6%	25%	1		2%	23%	1	
D2	6%	-3%	-9%	1	4%	-4%	-5%	1

Numbers in light blue are the main differences with the previous correlation table. In particular, throughout the period A1 and B1 display a slight negative correlation, whose magnitude increases significantly if we consider only the central period. This difference was not so definite in the previous sample. Moreover, the correlation between D2 and A1 (in 2006-2010 and 2008-2010) has a different sign than in the FITD data. If we consider D2 without extreme values, differences in signs still remain, at least in the period 2008-2010.

Differences in the two samples should be taken into consideration. In particular, further analysis aimed at finding ratios that have a common pattern for the two samples should be considered.

1.4 Results

This section describes the results obtained in the four stages described in the section on methodology.

a) Investigation of the explanatory power of procedures currently applied at the FITD for the computation of risk-based contributions

The FITD computes risk-based contributions by looking at the values of the four ratios, as specified in Table 1.4. In order to evaluate the explanatory power of the procedure, what happened in the period 2006-2010 was analyzed according to the four indicators.

Tables 1.19 and 1.20 summarize banks' distributions in the risk classes in the specified period:

Table 1.19: *Distribution of banks in the four risk classes associated with the four balance sheet ratios. FITD sample, 2006-2010*

A1	2006	2007	2008	2009	2010	Total
Normal	246	247	223	185	133	1034
Attention	11	11	20	35	40	117
Warning	4	5	7	15	27	58
Violation	2	2	2	5	8	19

Total	**263**	**265**	**252**	**240**	**208**	**1 228**

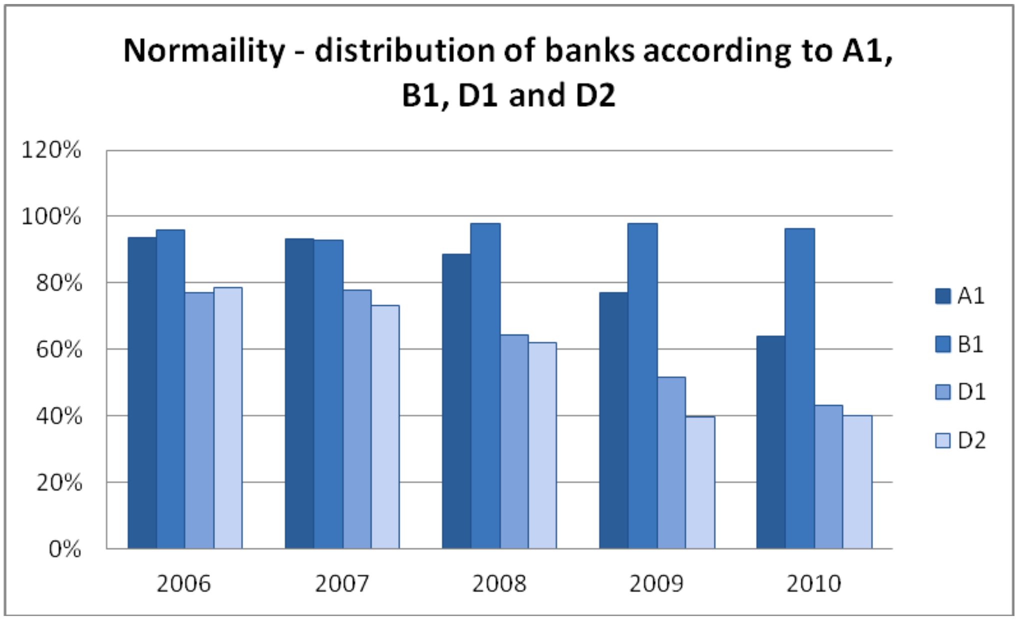
B1	**2006**	**2007**	**2008**	**2009**	**2010**	**Total**
Normal	252	246	247	235	200	1 180
Attention	11	13	2	2	2	30
Warning		4	1		2	7
Violation		2	2	3	4	11
Total	**263**	**265**	**252**	**240**	**208**	**1 228**

D1	**2006**	**2007**	**2008**	**2009**	**2010**	**Total**
Normal	203	206	162	124	90	785
Attention	23	19	33	50	56	181
Warning	17	12	17	21	21	88
Violation	20	28	40	45	41	174
Total	**263**	**265**	**252**	**240**	**208**	**1 228**

D2	**2006**	**2007**	**2008**	**2009**	**2010**	**Total**
Normal	207	194	156	95	83	735
Attention	5	12	20	27	20	84
Warning	4	6	14	20	19	63
Violation	47	53	62	98	86	346
Total	**263**	**265**	**252**	**240**	**208**	**1 228**

Ratios A1 and B1 rate the large majority of banks (more than 90 % of them) in the Normal risk class. This is a direct consequence of how thresholds for the identification of risk classes are fixed. In contrast, D1 and D2 rate a smaller proportion of banks as normal, and this is particularly clear in the last two years, when the state of health of the banks analysed clearly deteriorated. In general, every ratio shows a worsening situation as time goes by, as highlighted in Figure 1.4. This is more evident for D1 and D2, where the number of banks placed in the Normal risk class falls from more than 200 to 90 and 83 respectively. A1 and B1 also suggest a deterioration of banks' state of health, but the trend is less marked, in particular for B1 (banks in the Normal class fall from 252 in 2006 to 200 in 2010). It seems that A1 and (significantly) B1 lead to more optimistic evaluations of Italian banks during the period considered. Their behaviour should be better addressed in order to determine whether a (partial) modification of the model applied at the Italian DGS is needed.

Figure 1.4: *Distribution of banks in the Normal class according to A1, B1, D1, D2. FITD sample, 2006-2010*



The deterioration of banks' balance sheets is clear also looking at the aggregate indicator, as shown in the following table:

Table 1.20: *Aggregate indicator, distribution of banks in the six risk classes during the period 2006-2010. FITD sample*

	2006	2007	2008	2009	2010	Total
Normal	206	200	172	120	93	**791**
Attention	31	33	35	45	36	**180**
Warning	8	6	14	25	26	**79**

Penalty	17	23	25	43	43	**151**
Severe imbalance	1	2	4	5	5	**17**
Expulsion		1	2	2	5	**10**
Total	**263**	**265**	**252**	**240**	**208**	**1 228**

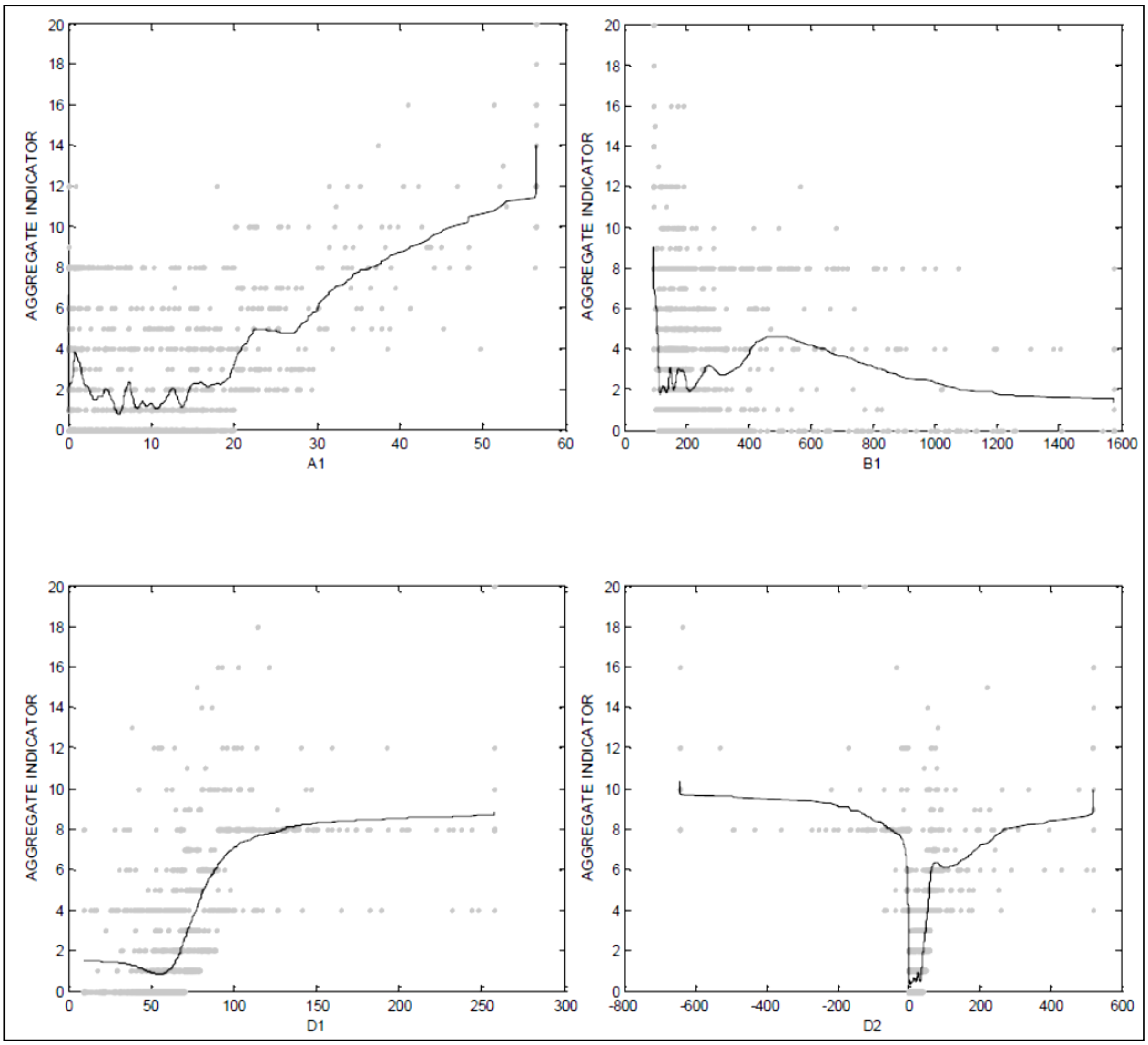
The deterioration of the situation is evident from the number of banks placed in the Normal class and the increasing number of banks in the Severe imbalance and Expulsion classes.

The reduction in the number of banks rated in the Normal class is obviously due to the financial turmoil starting in 2007, which caused a deterioration of banks' balance sheets, at least in those profiles captured by our indicators. Looking at individual ratios it is clear that A1 and B1 lead to more optimistic conclusions compared to D1 and D2. Moreover, B1 does not detect a significant change in banking riskiness during the period 2006-2010. In contrast, the other ratios indicate that both risk and profitability profiles are worsening during the years in question. These differences may originate from a real and deep difference in the four ratios, in the sense that the solvency profile of Italian banks, measured by B1, may not have been affected by the recent financial crisis. Alternatively, the construction of the aggregate indicator may suffer from some misspecification linked to the setting of thresholds for risk classes.

In order to better address this point, it is interesting to assess the importance of individual ratios for the composition of the aggregate index. Sensitivity analysis techniques are therefore applied here following both a graphical and a numerical perspective. The graphical point of view is explored using scatter plots in order to verify the existence of clear patterns in the relationship between the composite indicator (AI) and the sources of uncertainty (ratios and their aggregation). From a numerical point of view, first-order sensitivity indices for the four ratios are computed in order to understand whether the ratios employed significantly influence the construction of the aggregate indicator.

Figure 1.5 is composed of scatter plots: values of the aggregate indicator are represented on the vertical axis, while the horizontal axis represents individual ratios. The analysis is conducted over the entire period 2006-2010. In order to avoid the plots being influenced by extreme values, a winsoring procedure was applied such that extreme values at both the left and the right extremes of the distributions were replaced by the first available value considered as 'not extreme'.

Figure 1.5: *Scatter plots for A1, B1, D1 and D2*



B1 reveals a rather flat behaviour: the aggregate indicator seems not to be influenced by movements in B1. The other figures show a clear pattern in the relationship between the ratio and the aggregate indicator, giving evidence of their relative importance in the construction of the composite indicators. All of them have a rather monotonic behaviour, except for D2, which shows non-monotonicity caused by its peculiar construction: a bank is considered riskier either when D2 is negative or when it takes large positive values.

Numerically, we can investigate the informative power of each ratio through the first-order sensitivity index, explained in section 1.2. As mentioned earlier, its construction allowed us to compare the four ratios to see whether any of them is less useful than the others in the construction of the aggregate indicator. Sensitivity indices presented in Table 1.21 are calculated using the algorithm of Ratto and Pagano (2010).

Table 1.21: *Sensitivity indices associated with A1, B1, D1 and D2. FITD sample, 2006-2010*

	Sensitivity index
A1	0.4096
B1	0.0885
D1	0.4904
D2	0.7458

The analysis confirms that B1 lacks informative power. Furthermore, the important role given to A1 by its double weight is not confirmed here when we look at the associated importance measure, which is even lower than the one associated with profitability ratios.

Sensitivity analysis conducted on the actual FITD model reveals some critical issues connected in particular with the ratios A1 and B1. For this reason a partial revision of the methodology currently applied at the FITD would be useful.

A first solution could consist in modifying the thresholds associated with the ‘problematic’ ratios: A1 and B1. I decided not to follow this approach because my intention was not to propose a modification specifically tailored to the Italian system. The remainder of this contribution aims to provide a ‘guide’ that could be taken into consideration for future modification of European DGSs. I therefore propose a methodology based on market data, which are useful to calibrate the aggregation of ratios in an aggregate indicator. As confirmed in Chiaramonte and Casu (2010), CDS spreads and balance sheet ratios are strictly linked, so I chose to investigate the relationship between such data and FITD ratios. Here I had to use a different sample of banks for which FITD ratios are constructed. As shown in section 1.3, the two samples have different characteristics over the period considered. For this reason, the present contribution represents only a starting point for future research on DGS methodologies. Further efforts in finding different samples and in investigating different balance sheet ratios are certainly needed.

b) Investigation of the relationship between CDS spreads and balance sheet ratios used at the FITD in a sample composed of 48 European banks issuing CDSs

To determine whether CDS spreads can be explained by balance sheet ratios, a panel data regression was used in which the explanatory variables are represented by balance sheet ratios and the dependent variable is the CDS spread, as shown in the equation below:

$$CDS_{jt} = \beta x_{jt} + \varepsilon_{jt}$$

Regressions were conducted over the sample of 48 EU banking groups, for which the four FITD ratios were constructed using Bankscope data.

As a first step, two regressions were performed over the entire period 2006-2010: one regression includes the four FITD ratios and the second one includes also a dummy variable that identifies the last three years, these being the most turbulent years according to CDS values (we can call them the core crisis period). Subsequently regressions were run specifically on those three years. For all the regressions the final sample consists of 165 observations for 48 banks (years with missing data were eliminated).

The results are set out in Table 1.22:

Table 1.22: *Panel regressions, Bankscope sample*

	2006-2010	**2006-2010 with dummy**	**2008-2010**
A1	0.0455*** (0.0054)	0.0413*** (0.0053)	0.0442*** (0.0066)
B1	0.0056 (0.0049)	-0.00055 (0.0048)	0.0064 (0.0062)
D1	-0.00062 (0.0112)	-0.00208 (0.0169)	0.0049 (0.0141)
D2	-0.00018 (0.00016)	-0.0002* (0.00016)	-0.00017 (0.0002)
Dummy		1.862*** (0.0068)	
Number of observations	165	165	110
Number of sample banks	48	48	48
Adjusted R-squared	0.4623	0.4813	0.4807

Notes: The dependent variable is CDS spreads, which measures the probability of default. The explanatory variables are four balance sheet ratios referring to the risk profile (A1), the solvency profile (B1) and the profitability profile (D1 and D2). Standard errors of estimated coefficients are given in brackets.
*** denotes coefficients statistically different from zero (1 %, 2.5 %, 5 % levels)

The four balance sheet ratios explain nearly 46 % (2006-2010) to 48 % (2008-2010) of bank CDS spreads (adjusted R-squared), confirming what was found in previous research. Almost the same result is obtained considering the four ratios together with the dummy variable: they explain about 48 % of CDS spreads. Comparing different regressions it emerges that, despite the fact that the dummy is significant at the 1 % level, there are not large differences between the regression performed on the period 2006-2010 and the one referring only to the central crisis period.

Looking at significance levels, it emerges that A1 is the most significant variable. The high explanatory power of A1 was expected since it is the ratio focused on the credit risk and CDSs are strictly linked to that specific banking risk. B1 became significant over the 10 % level and the introduction of the dummy makes its significance level decrease. D1 is never significantly different from zero (the t-statistic ranges from -0.055 in the first regression to 0.349 in the regression with the dummy).

Only A1 has the expected sign in all the regressions performed. B1 shows the expected sign (negative) only in the regression involving the dummy, whereas D1 has a positive sign only in the last regression. Since D2 has non-monotonic behaviour, the ratio is modified by replacing D2 negative values with the 95th percentile of its distribution.

Table 1.23: *Panel regressions with modification of D2. Bankscope sample*

	2006-2010	**2006-2010 with dummy**	**2008-2010**
A1	0.0469^{***}	0.0428^{***}	0.046^{***}
	(0.0055)	(0.0055)	(0.0067)
B1	0.00522	-0.0015	0.0061
	(0.0049)	(0.0053)	(0.0061)
D1	0.0015	0.0005	0.0081
	(0.017)	(0.0111)	(0.0142)
D2	-0.00027	-0.0003^{*}	-0.0003
	(0.00018)	(0.00018)	(0.0002)
Dummy		2.009^{***}	
		(0.7058)	
Number of observations	165	165	110
Number of sample banks	48	48	48
Adjusted R-squared	0.465	0.487	0.487

The partial modification of D2 makes it possible to slightly increase its significance (it is always significant at the 10 % level, but it reaches significance at 5 % only in the regression with the dummy). But still there are not large differences between the two regression results.

As can be seen, the dummy variable is again highly significant, demonstrating that the crisis was a relevant event in the relationship between CDS spreads and balance sheet data.

Looking at signs, A1 and D1 show the expected relationship with CDS spreads, and B1 shows a negative relationship with CDS spreads only in the regression involving the dummy, as in the previous case. D2 always shows a negative relationship with the dependent variable.

Looking at the results the following observations can be made:

- A1, which represents the credit risk profile, is the ratio mostly connected to CDS spreads. So, a DGS system that wants to emphasise the bank's capacity to face losses without becoming insolvent should give more importance to the balance sheet indicator connected with credit risk. The choice of the Italian DGS to assign more importance to A1 through a double coefficient should be evaluated taking this reasoning into account.
- B1 loses importance with the introduction of a dummy variable identifying the most turbulent crisis period. Without the dummy variable, B1 is significant at the 20 % level (with and without the modification of D2).
- D1 appears to be not significantly different from zero. In the first set of regressions, the sign of its relationship with CDS spreads doesn't emerge clearly. With the introduction of a modified version of D2, its sign is always positive, but its significance doesn't improve. Even if this ratio measures the same bank profile as D2 (efficiency/profitability), it cannot be discarded from the analysis. Looking at low correlations between D1 and D2 it is clear that the two ratios do not measure the same riskiness profile, so D1 doesn't seem to be redundant. Further research on this ratio is needed.
- D2 has a non-monotonic behaviour that calls for a partial modification. By design, high riskiness is measured either by negative values (thanks to the denominator) or by large positive values. The negative values were transformed into the positive values that represent the 95th percentile of D2's distribution. After this modification, D2 is always

significant at the 10% level and at the 5% level with the introduction of the dummy variable. Nevertheless, regression coefficients always have a negative sign, which was not expected.

- The four ratios explain about 48% of CDS spreads. This result confirms what was found by previous literature: CDS spreads are strictly connected with balance sheet ratios. For this reason, they can be used as a benchmark for composite indicators intended to represent banks' riskiness.
- The choice of balance sheet ratios needs to be better explored. Taking into account previous literature, it emerges that liquidity and leverage are not considered in the current Italian model. The present contribution aims to propose a critical approach to existing DGSs: comparing current approaches using balance sheet ratios with quantities priced on the market is useful to gain an idea of what kind of situation is actually measured.

Considering the regression coefficients presented earlier, it is possible to construct an aggregated indicator of banking riskiness for the 48 EU banks issuing CDSs and using the same coefficient to construct another indicator for the FITD sample.

c) Construction of an alternative indicator of (Italian) bank riskiness using regression coefficients found in the previous step

d) Comparison of the performance of the new indicators with the current indicator applied in the Italian DGS

The coefficients found in the first and second group of regressions for the whole of the period 2006-2010 were selected and an aggregate indicator was constructed for bank riskiness that assigns the following weights:

- 8 to A1

- 1 to B1
- -0.05 to D1
- 0.05 to D2.

Coefficients were chosen taking into account the magnitude of the four coefficients found in the above regressions.

When D2 is modified to eliminate negative values, the coefficient associated with D1 changes sign and becomes 0.05.

The two aggregate indicators are constructed for the sample composed of 48 EU banks and two series are obtained that exhibit a correlation with the CDS spread series of, respectively, 55 % and 56 %.

The following table shows the average values of the two aggregate indicators and of the CDS spreads over the five years considered:

Table 1.24: *Annual average values of aggregate indicators and CDS spreads over 2006-2010. Bankscope sample*

	Average values		
	CDS spreads	**AI**	**AI with D2 modified**
2006	0.143	288.651	294.550
2007	0.821	292.772	298.875
2008	3.872	498.843	469.815
2009	1.981	533.881	513.548
2010	5.285	653.809	637.203

Note: the last column refers to results obtained with the D2 series obtained by replacing negative values with the 95th percentile of D2's distribution.

The two aggregate indicators show a clear increasing trend over the five years considered. Nevertheless, in terms of magnitude, there is not the same rise in ratios as in CDS spreads.

Applying the same weights for the four indicators constructed for the FITD sample yields the following values:

Table 1.25: *Annual average values of aggregate indicators over 2006-2010. FITD sample*

	Average values	
	AI	**AI with D2 modified**
2006	328.641	332.948
2007	363.187	368.163
2008	355.499	359.994
2009	361.702	368.425
2010	398.036	392.298

The increasing trend is evident also taking the FITD sample, with the exception of 2008, when there is a decrease in average values.

My last step was to make a comparison between the AI obtained using CDS spreads and the current Italian AI. For this purpose the following table was constructed that highlights the behaviour of new aggregate indicators in the six classes of risk identified by the aggregate indicator currently used at the FITD.

Table 1.26: *Annual average values of the new aggregate indicator in the six risk classes identified by the aggregate indicator currently used at the FITD. FITD sample, 2006-2010*

	Average AI				
	2006	**2007**	**2008**	**2009**	**2010**
Normal	316.058	320.280	330.506	332.971	358.122
Attention	358.214	534.453	388.798	376.513	332.632
Warning	300.894	277.504	390.245	346.656	389.634
Penalty	428.445	513.517	426.075	396.660	462.995
Severe imbalance	529.237	267.311	431.414	538.230	775.293
Expulsion	-	541.097	644.949	747.514	719.131
Tot. average	328.641	363.187	355.499	361.702	398.036

Table 1.27: *Annual average values of the new aggregate indicator (obtained with D2 modified) in the six risk classes identified by the aggregate indicator currently used at the FITD. FITD sample, 2006-2010*

	Average AI (with D2 modified)				
	2006	**2007**	**2008**	**2009**	**2010**
Normal	321.542	325.703	336.332	339.197	364.701
Attention	361.202	539.048	394.819	386.692	339.174
Warning	307.755	282.497	397.705	353.890	397.012
Penalty	419.983	514.861	423.124	400.384	464.905
Severe imbalance	528.697	274.060	399.484	545.874	403.320
Expulsion	**-**	549.141	653.367	762.018	628.146
Tot. average	332.948	368.163	359.994	368.425	392.298

Looking at the above results it is clear that both the new aggregate indicators exhibit an increasing trend along the risk order defined by the six risk classes. The AI rises in the six risk classes with the exception of 2007, when both AIs show fluctuating behaviour. A closer look at original data reveals that such behaviour is caused by the ratio B1, which in 2007 takes on really extreme (positive) values for ten banks, probably because of the beginning of the crisis. In particular, averages are influenced by extremes in the Normal, Attention and Penalty classes that for this reason take on really high values. The exclusion of extreme values for B1 allows an increasing trend to be obtained also for the year 2007.

For the same reason the annual average values (reported also in Table 1.25) do not increase monotonically: the large rise in 2007 is driven by the ten extreme values of B1.

The behaviour of annual average values of the new AI shows that the current Italian model and the AI derived from CDSs go in the same direction. This is not so evident looking at minimum and maximum values of new aggregate indicators: they do not rise univocally along risk classes and they show huge variability.

1.5 Conclusions

This chapter is focused on the Italian DGS with the aim of examining its methodology to compute risk-based contributions. Its explanatory power during the period 2006-2010 is investigated and it reveals some weaknesses connected to two out of four balance sheet ratios.

Recent literature about CDS highlights that there is a significant relationship between CDS spreads and balance sheet ratios. This chapter starts from these findings and it proposes a critical revision of the model currently adopted at the FITD based on the relationship between CDS spreads and the FITD's four balance sheet indicators. Panel regressions were conducted using a sample composed by EU banking groups issuing CDS. The four balance sheet ratios were constructed for the 48 banks in this sample and results show that the ratio A1, that is closely related to the credit risk profile, is the mostly connected to CDS spreads. B1 also shows a significant role in explaining CDSs whereas D1 and D2 seem less important in explaining CDS spreads. Using the regression coefficients, a new aggregate indicator (AI) for the FITD sample is then constructed. The comparison between the new AI and the old AI reveals that they go in the same direction, at least during the considered period.

Results confirm what was found by previous literature: CDS spreads are strictly connected to balance sheet ratios. This should represent a starting point for a partial revision of methodologies currently adopted in EU DGS in order to link their procedure to the risk actually priced on the market.

The procedure applied here shows also some weaknesses: the sample composed by the 48 EU banks and the one composed by Italian banks provided by the FITD exhibit different characteristics in terms of balance sheet ratios' trends during the period 2006-2010. Moreover, banks issuing CDSs are generally mid-tier and top-tier banking groups, whereas in the FITD dataset there are individual banks with different dimensions. This point should be better addressed in future research: results emerging in this chapter could be validated extending the analysis in different EU countries.

The analysis of the adequacy of ratios used at the FITD goes beyond the scope of this chapter. Nevertheless, a further analysis about the relationship between CDSs and balance sheet ratios currently used in other EU DGS as well as the ones employed in the US is of crucial importance.

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Chapter 2

How can we measure the impact of banks' balance sheets on public finances?

2.1 Introduction

The current financial crisis originated in the US in mid-2007 but gave rise to serious implications for Europe starting from September 2008, when the investment bank Lehman Brothers went bankrupt. In order to ensure the liquidity of the financial system, European central banks, the ECB and Member States (MSs) took several emergency measures that had stability and soundness of the financial system as their main objective. European G8 members at their summit in Paris on 4 October 2008 jointly committed to take all the necessary measures to achieve this objective. The leaders of all 27 EU countries agreed on a similar statement on 6 October 2008 and on reinforcing bank deposit protection schemes. At the Ecofin Council on 7 October 2008 the Member States' finance ministers agreed that the priority was to restore confidence and the proper functioning of the financial sector; they all undertook to do whatever was necessary to enhance the soundness and stability of banking systems and to protect the deposits of individual savers. To that end, they agreed on EU common principles to guide their action and on the need to recapitalise vulnerable systemically important financial institutions. At the same time, the Ecofin Council agreed that all Member States should provide a deposit guarantee for individuals of at least €50 000, acknowledging that many Member States intended to raise their minimum to the €100 000 level. Subsequently, at the summit of the euro area countries held on 12 October 2008, participants adopted a European Action Plan underlining the need for a coordinated approach among European Union and euro area governments, central banks and supervisors aimed at:

- ensuring appropriate liquidity conditions for financial institutions;
- facilitating the funding of banks;
- providing financial institutions with additional capital resources so as to continue to ensure the proper financing of the economy;
- allowing for an efficient recapitalisation of distressed banks;

- ensuring sufficient flexibility in the implementation of accounting rules given current exceptional market circumstances;
- enhancing cooperation procedures among European countries.

Following the above plan, Member States adopted measures at national level to support their financial systems and ensure appropriate financing conditions for the economy, with particular attention to confidence and liquidity in their banking systems.

To what extent do the measures listed above require the involvement of government finances? The current crisis has shown that the balance sheets of governments and of banks are interconnected, and each can affect the other. A change in the value of sovereign bonds can, for example, affect banks, as high-grade government bonds are used by the Eurosystem banks as collateral to obtain liquidity from the ECB, with the amount of the liquidity being dependent on the grading of the assets. Given the high integration of capital markets, any downgrading of a sovereign in the euro area can have broad spillover effects on Eurosystem banks. As clearly stated in the speech by Hervé Hannoun (Financial Stability Institute High-Level Meeting) the recent period has seen a rise of sovereign risk in financial markets that is reflected in sovereign CDS premia as well as in sovereign rating downgrades. For this reason, sovereign assets are no longer risk-free and, as a consequence, they are no longer zero-credit. The resulting risk for banks emerges from data about their sovereign exposures, published e.g. in the BIS quarterly review for the first quarter of 2011:[1]

Table 2.1: *BIS data on foreign claims on the public sector in selected countries (billion USD, end-Q1-2011)*

		Foreign claims on					
	Belgium	**Greece**	**Ireland**	**Italy**	**Portugal**	**Spain**	**Total**
Euro area	81.1	38.3	9.8	215.4	30.1	80.1	454.8

[1] For further details on EU banks' sovereign debt exposures, see Blundell-Wignall and Slovik (2010).

Bank nationality	France	51.5	13.4	2.9	105.0	8.6	32.6	214.0
	Germany	11.3	14.1	3.2	51.0	8.8	29.4	117.7
	UK	5.3	4.0	4.6	12.7	1.8	8.6	37.0
	US	11.4	1.9	1.7	14.4	1.3	6.1	36.8
	Japan	9.4	0.2	1.1	29.8	1.1	10.4	51.9

Notes: foreign claims consist in cross-border claims and local claims of foreign affiliates. Not included are the bank claims on their home sovereign.

Source: BIS consolidated banking statistics and speech by Hervé Hannoun.

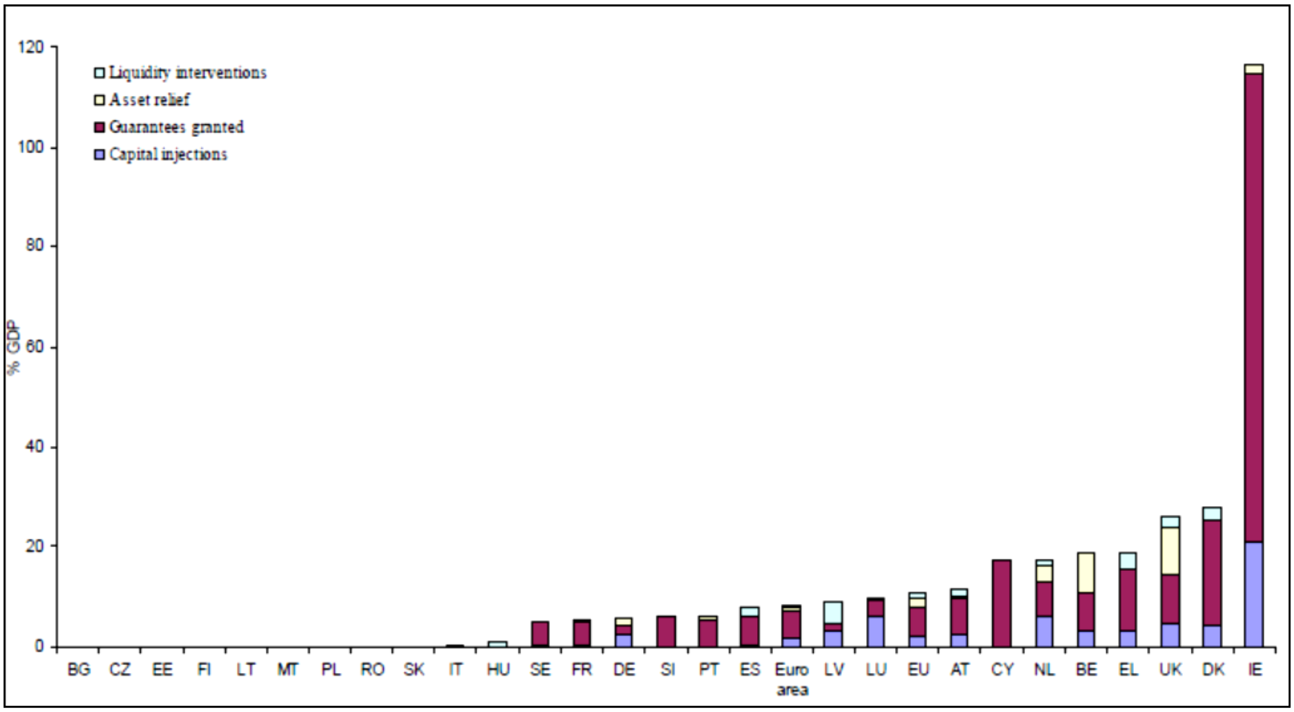
On the other side, government finances can be directly or indirectly affected by banks' balance sheets. The support provided by the government to the banking system typically entails a direct upfront rise in government debt as well as indirect fiscal consequences.[2]

This chapter focuses on direct consequences of the state of health of the financial sector on government finances. In particular, losses for public finances are measured using the model developed by De Lisa et al. (2010) that allows to simulate failures in banking systems with different regulatory settings and to evaluate the magnitude of losses originated by banks' defaults.

As reported in European Commission (2011), since the outbreak of the crisis, governments and central banks have been involved in the rescue of failing banks via state aid, albeit to a different extent in different countries. As Figure 2.1 shows, government assistance to the banking sector has, overall, been sizeable and in more than half of the Member States has exceeded 5 % of GDP. Currently, sizeable rescue measures for the banking sector weigh heavily on public finances, most particularly in Ireland, the UK, Denmark, Belgium, the Netherlands, Austria and Germany.

Figure 2.1: *EU public intervention in the banking sector*

[2] A good summary of the general discussion on government intervention during the subprime mortgage crisis can be found on the Wikipedia webpage
http://en.wikipedia.org/wiki/Government_intervention_during_the_subprime_mortgage_crisis



Source: EFC questionnaire (based on data from 31/12/2009), updated to 31/10/2010

We know that government assistance to the banking sector tends to be a combination of various measures such as capital injections, asset purchases and direct lending by the treasury, liquidity provisions and guarantees.

Through capital injection, a bank facing liquidity or solvency problems receives capital, either via a national scheme or via an ad hoc individual rescue operation in order to restore required capital ratios. As explained in IMF (2009), governments and some central banks have provided substantial direct loans and have purchased illiquid assets from financial institutions during the current financial crisis. Liquidity support interventions are measures aimed at supporting liquidity and providing extra financing to the bank via a state guarantee. This includes a broad range of interventions, such as credit lines to financial institutions, purchase of asset-blocked securities and commercial papers, and asset swaps. Liquidity support interventions during recent years were sizeable in many non-euro area countries, as these countries did not have access to the ECB's liquidity. Within the euro area, some banks were also able to avail themselves of their national central banks' emergency liquidity assistance (ELA). Regarding guarantees, they can be provided for bank liabilities: deposits, interbank loans and, in some cases, bonds. IMF estimates about the amount of support measures for the financial sector during the current crisis can be found in IMF (2009).

As compared to the overall amounts of EU domestic public interventions, financial assistance and rescue package measures have been significantly smaller in most of the new Member States. This is due to deleveraging and increased risk aversion on their financial sectors as well as to the dominant presence of foreign-owned banks. The parent banks of these subsidiaries and branches maintained the exposures and provided additional capital as required.

A complete evaluation of public interventions should take into account also the extent to which the assets acquired by governments or central banks will hold their value and can be disinvested without losses. As explained in IMF (2009), recovery rates depend on the type of intervention, the approach followed in managing and selling the assets and various economic factors. Econometric analysis shows that recovery rates are positively correlated with per capita income and with the strength of the fiscal balance at the start of any crisis.

The cost of public intervention depends also on exit strategies that governments adopt to reduce their involvement in the financial system once the situation returns to normal. Exit strategie should be declared in advance by governments in order to ensure that solvency is not at risk. In this way adverse market reactions are avoided.

As explained in ECB (2010), in past banking crises concrete exit strategies were rarely specified *ex ante* and recovery rates tended to be well below 100 %.

European Commission (2011) clarifies that currently, exit strategies from public support to banks have been initiated. However, the situation differs across Member States as, in some countries such as the Netherlands, France and Austria, banks have started to repay the state aid, while in other countries government assistance to the financial sector was provided only recently.

However, in most countries where the banks have received state aid, the financial system remains fragile. This means that the exit from crisis support measures will need to be carefully managed between the need to safeguard macro-financial stability and the need to preserve fiscal credibility. In some countries banks' profitability outlook is uncertain given a sluggish recovery, heavy exposures to the real estate sector and tensions in the sovereign debt market. This could signal that directly or indirectly — via reduced growth — the costs to government finances are unlikely to be reduced in the near term.

On the basis of the above considerations, the importance of quantifying the effect that a banking system faced with financial difficulties could have on the stability of government finances is clear.

Some recent papers analyse the intervention policies at country level put in place to mitigate the effects of the crisis. Schich (2010) compares the *ex ante* funding of deposit guarantee schemes (DGSs) in a selection of countries, highlighting the 'funding gap' left by these arrangements in the current financial crisis. This gap derives directly from the fact that DGSs are designed to cover the costs of discrete failures in normal times: in the event of systemic crises, their funding proves inadequate. Taxes or levies collected with the purpose either of financing systemic risk resolution or of reducing systemic risk can fill the funding gap. To this extent, the Swedish and German *ex ante* approaches appear in principle to be suited to helping ensure more adequate funding.

Assessing the efficiency of all the possible intervention measures makes it necessary to accurately quantify the damage potentially caused by a systemic banking crisis. Once funding needs are quantified in different financial scenarios, more effective policy measures can be devised.

This chapter will present the results of an estimation of the direct potential impact of bank losses on government finances, which has been developed to address these issues. The analysis is based on the results of the SYMBOL (**SY**stemic **M**odel of **B**anking **O**riginated **L**osses) model for evaluating the probability distribution of the systemic losses in the banking sector which may potentially affect government finances. The model is developed in De Lisa et al. (2010). It starts by estimating the probabilities of default of bank obligors as assessed by the country's banking system regulator. It then uses these estimates to evaluate the default risk of individual banks, and aggregates individual bank losses to estimate the distribution of losses for the banking system as a whole. This aggregate distribution by country can be obtained under different conditions. By considering different regulatory regimes and the risks they entail, an estimate of possible costs to public finances is then computed in the various conditions considered.

A major strength of the model is the fact that it uses publicly available information to estimate each bank's portfolio riskiness and to compute a probability distribution of aggregate bank losses. SYMBOL is consistent with Basel regulations and its flexible construction makes it possible to explicitly consider banks' asset correlation and contagion effects driven by interbank exposures. Clearly, the methodology also has some weaknesses. First, publicly available data on the banking system do not have sufficient coverage in all EU countries. Second, the model's calculations rely on how regulators model banks' losses when computing capital requirements. Third, the model does not directly include a link to the general economic situation. Finally, banks' capital requirements are not only composed of their credit risk component (although credit risk is normally a very preponderant part of capital requirements), while SYMBOL currently assumes that all bank assets consist entirely of loans, so that all capital requirements are considered as for credit risk. SYMBOL is used here to generate three indicators of financial stability: the probability that public finances are hit by losses deriving from bank defaults, the distribution of costs for public finances and the probability that, due to a banking crisis hitting public finances, a Member State becomes high risk. Results have been published in the report Public Finance in EMU by European Commission (2011) in the chapter dedicated to debt sustainability in EU.

The rest of the chapter is structured as follows: section 2.2 reviews existing literature about both the impact of banking crises on government expenditure and models for evaluating the probability distribution of losses in banking systems. Section 2.3 explains the methodology used, while the input data are presented in section 2.4. Section 2.5 sets out the results, which are expressed as three different indicators of sustainability. Conclusions, model weaknesses and ideas for further research are outlined in section 2.6.

2.2 Literature review

Referring to the EU context, most of the papers that focus on identifying the fiscal costs associated with financial crises have originated from within the EU institutions. They are all based on an *ex post* quantification of the damage that past episodes of financial turbulence have caused in terms of fiscal costs. No one provides forecasts on the involvement of public finances in the resolution of crises. For that reason, this chapter represents a good starting point in an unexplored strand of research.

Caprio and Klingebiel (1996) collect data about bank insolvencies that occurred in the period from late 1970 to 1996. They give details about the country, the scope of the crisis, the estimation of losses, magnitude, resolution mechanisms, GDP (the main characteristics of banking crises), financial deepening, real credit, real deposit interest rates (financial analysis of crisis countries), the terms of trade in crisis countries, and the characteristics and outcome of restructuring. The authors conclude that widely available indicators of bank performance are lacking. Relatively few countries scored well on handling bank insolvency and insolvencies seem most costly in recent times. The dataset has been updated since 2006 (see Caprio et al., 2005).

Eschenbach and Schuknecht (2002) analyse the fiscal costs of financial instability, which is defined as a period of large asset price swings possibly leading to a financial crisis. They identify three transmission channels by which asset price changes and financial instability affect fiscal costs: capital gains taxes and wealth-based taxes, capital transaction taxes, and wealth effects on consumption (hence indirect taxes). The authors find such effects significant in many OECD countries. In a next step they look at public debt developments as an alternative measure of the fiscal costs of financial instability during a number of financial instability episodes in industrialised countries. Public debt increased by 10 to 50 % of GDP during such episodes. Large asset price changes and financial instability can have major effects on fiscal accounts, raising the variability of fiscal accounts and the public debt ratio. Especially in episodes defined as ‘financial crises’ and when the debt stock at the outset is high, the rapid and major deterioration of the fiscal deficit and the strong increase in public debt can undermine the stability and sustainability of public finances.

Reinhart and Rogoff (2008) provide an overview of the history of financial crises from the mid-14th century to the 2008 subprime crisis. They introduce a comprehensive dataset for studying international debt and banking crises, inflation, and currency crashes and debasements. Data refer to external and domestic debt, trade, GNP, inflation, exchange rates, interest rates, and commodity prices. They cover 66 countries in Africa, Asia, Europe, Latin America, North America and Oceania. The authors discard the idea that ‘this time it’s different’ applied to the current financial crisis, showing that cycles of euphoria and subsequent fall are quite common in history.

Reinhart and Rogoff (2008b) employ a small piece of the historical dataset constructed for their previous paper. They compare the 2007 US crisis with previous episodes (18 bank-centred financial crises from the postwar period), specifically looking at asset prices, real economic growth, and public debt. They conclude that, while each financial crisis is distinct, they also share similarities in the run-up in asset prices, debt accumulation, growth patterns, and current account deficits.

In a subsequent paper, Reinhart and Rogoff (2009) analyse the aftermath of financial crises by examining the duration of the slump that follows severe financial crises, with particular attention to effects on asset prices, output and employment. More often than not, the aftermath of severe financial crises displays the following three characteristics: deep and prolonged asset market collapse, deep decline in output and employment and explosion of government debt. Regarding the last point, the main cause of debt explosion is not the costs of bailing out and recapitalising the banking system but the collapse in tax revenues related to output contractions and countercyclical fiscal policies put in place to mitigate the downturn.

Furceri and Zdzienicka (2010) focus on the debt-to-GDP ratio. Looking at several episodes of banking crises during the period 1980-2006, they quantify the development of the government gross debt-to-GDP ratio in the aftermath of banking crises. They estimate impulse response functions of public debt to banking crises for 154 countries. They find that banking crises have produced a significant and long-lasting increase in the government debt-to-GDP ratio, with the effect being a function of the severity of the crisis, measured in terms of output losses. They also find that the increase in public debt strictly depends on country-specific characteristics.

Laeven and Valencia (2010) create a database containing starting dates and characteristics of systemic banking crises over the period 1970-2009. A banking crisis is defined as systemic if two conditions are met: there are significant signs of financial distress in the banking system and significant banking policy intervention measures are taken in response to losses in the banking system. Policy interventions are significant if at least three out of six measures have been used (liquidity support, defrayment of bank restructuring costs, bank nationalisation, guarantees, asset purchases, deposit freezes and repayment holidays). The authors also provide an estimate of the costs of the 2007-2009 systemic banking crisis using three metrics: direct fiscal costs (fiscal outlays committed to the financial sector from the start of the crisis up to end-2009), output losses (deviations of actual GDP from its trend) and increases in public sector debt relative to GDP (change in the public debt-to-GDP ratio over the four-year period beginning with the crisis year). They find that output losses can be very substantial. The cumulative difference between actual and trend real GDP often amounted to 20 to 40 % of a country's annual GDP.

In a paper published in 2010, the ECB analyses the response of euro area fiscal policies to the current financial crisis and the direct impact of government support to the banking sector on euro area public finances. Initially, public support was oriented to the liability side of banks' balance sheets and consisted of three kinds of measures:

- government guarantees for interbank lending and new debt issued by the banks;
- recapitalisation of financial institutions in difficulty (including injections of government capital and nationalisations);
- increased coverage of retail DGSs.

Although the MSs have endorsed the European Action Plan, the European Commission's Communications and the ECB guidelines, specific characteristics of the measures adopted differ among countries.

In early 2009 public support began to target the asset side of banks' balance sheets. It consisted of:

- impaired asset removal schemes (through direct government purchases or by transferring them to independent asset management companies);
- asset insurance schemes, that kept the assets on the banks' balance sheets but insured them against tail risk.

Asset relief schemes are regulated by the Eurosystem Guiding Principles for Bank Support Schemes, issued by the Eurosystem and the European Commission in February 2009.[3]

The impact of government support is assessed on the basis of statistical recording principles spelt out in the ESA 95. Eurostat is now developing further methodologies: it has consulted the Committee on Monetary, Financial and Balance of Payments Statistics (CMFB) to determine how the accounting rules should be applied. The CMFB compiled a number of recording principles for intervention measures.

In order to assess the net fiscal costs of government support to the banking sector, ECB (2010) takes into account two channels: the direct impact and the fiscal risk. Regarding the direct impact, they analyse both the net impact on government deficits (below 0.1 % of GDP for the euro area as a whole) and the increase in euro area government debt on balance due to stabilisation measures

[3] See www.ecb.int/pub/pdf/other/guidingprinciplesbankassetsupportschemesen.pdf

(2.5 % of GDP by the end of 2009).[4] Regarding the other channel, they highlight that governments have assumed two fundamental types of fiscal risk as a result of the financial crisis: one related to the governments' liabilities and the other linked to the effects of financial sector support measures on the size and composition of governments' balance sheets. By the end of 2009, the implicit contingent liabilities related to rescue measures represented at least 20 % of GDP for euro area governments. The explicit contingent liabilities that were actually provided to banks and special-purpose entities on balance amount to about 9.4 % of GDP. Looking at the effect on governments' balance sheets, in theory support interventions do not increase governments' debt. In practice, their impact depends on their management and experience shows that recovery rates are usually below 100 %.

This contribution takes a quite different perspective: instead of dealing with *ex post* evaluation it looks at forecasting. My interest is in assessing the sustainability of banking crises in terms of public finances, and I therefore need a tool that acts as a simulator of banking crisis scenarios. There are two methodologies currently used to model defaults: the fictitious default algorithm developed by Eisenberg and Noe (2001) and the sequential default algorithm devised by Furfine (2003). Both methods start from the artificial failure of a bank j and then count losses due to sequential failures. The main difference between them is that the first method takes into account the simultaneity problem (defaults occurring after the trigger may increase losses at the banks that have failed previously), whereas the second one does not. In this chapter I use the model developed by De Lisa et al. (2010) based on Monte Carlo (MC) simulations.

In the existing literature, MC simulations for banking defaults are provided only in two contributions (Elsinger et al., 2006 a, b). The first paper analyses the ten major UK banks in order to outline a framework for systemic financial stability that can capture correlated exposures and credit interlinkages. Starting from an initial state of the banking system described by balance sheet and market data and assuming a stochastic process for bank assets, they simulate via MC

[4] IMF (2010) estimates that the fiscal costs of direct support, net of amounts recovered so far, average 2.8 % of GDP

the net income of each bank and interbank exposures, thereby characterising the entire banking system. If, for a given net income and net interbank position, the total value of a bank becomes negative, the bank is insolvent. The authors perform 100 000 scenarios, and the vast majority of them (more or less 95 % of cases) do not involve any defaults.

The second paper uses a network model of interbank loans to assess systemic financial stability in the Austrian banking system. The authors use the Eisenberg and Noe algorithm (2001) modified in order to take account of uncertainty. They assume that each bank has portfolio holdings composed of interbank credits, loans, bonds and stocks on the asset side and interbank debts and liabilities to non-banks on the liability side. These positions are exposed to market and credit risk, so they generate scenarios[5] and compute losses on banks' portfolio holdings. Interbank connections are endogenously explained by the network model.

The approach developed by De Lisa et al. (2010) was originally devised to extend the existing literature on deposit insurance by proposing a different estimation of the loss distribution of a DGS based on the Basel II regulatory framework. The existing literature on estimating the optimal size of a DGS's funds proposes two alternative methodologies: one based on option pricing theory (see for example Kuritzkes et al., 2005 for the US and Sironi and Zazzara, 2004 for Italy) and the other adopting a reduced-form model drawn from the pricing of fixed-income securities under default risk (see Duffie et al., 2003). Both approaches are based on structural models for credit risk, which generally require market data in order to empirically apply the proposed methodology. Except for De Lisa et al. (2010), no one else thus considers the link between banks' capital requirements and the shape and size of DGS loss distribution. The authors first estimate the DGS loss distribution taking into account Basel II capital requirements. They then take into account the impact of systemic risk that they assume is generated by two sources: the correlation of banks' assets and interbank contagion.

for advanced G20 countries.

[5] For market risk the authors use the joint distribution of risk factors (FX, interest rate, stock market changes). For credit risk, they employ an extension of the CreditRisk+ Model.

SYMBOL is designed so that it can incorporate changes due to intervention measures. Regulatory interventions such as the raising of banks' capital levels, the modification of deposit guarantee schemes or the establishment of a resolution fund can be incorporated in the framework. In this way it is possible not only to evaluate their (individual or combined) effects in different simulated scenarios but also to quantify banking losses that have an impact on public finances because they cannot be absorbed by safety net tools.

Some recent scientific contributions analyse policy measures put in place either for funding systemic crisis resolution or for reducing systemic risk. Schich (2010) gives an overview of selected policy measures in the following table:

Table 2.2: *Categorisation of selected policy measures for funding systemic crisis resolution*

<table>
<tr><th></th><th></th><th>Revenue raising</th><th>Corrective</th></tr>
<tr><td rowspan="3">Funding systemic crisis resolution</td><td>Ex ante funding for future crisis</td><td colspan="2">Sweden: Stability Fund
Germany: Restructuring Fund
EC: Bank Resolution Fund
IMF: Financial Stability Contribution</td></tr>
<tr><td rowspan="2">Ex post revenue generation for general budget</td><td colspan="2">United States: Financial Crisis Responsibility Fee
Hungary: Bank levy
UK: Bank levy
Austria: Bank levy
France: Bank levy</td></tr>
<tr><td colspan="2">UK: Bank Payroll Tax
France: Temporary Bonus Tax
Italy: Permanent Bonus Tax
IMF: Financial Activities Tax</td></tr>
</table>

Source: Schich (2010)

The author concludes that arrangements such those introduced in Sweden and Germany are suited in principle to helping ensure more adequate funding.

IMF (2009) provides an assessment of the short- and medium-term outlook for public finances. Taking into account intervention measures announced by different countries and assuming different recovery rates (depending on the nature of the support), the authors projected fiscal balances and debt-to-GDP ratio up to 2014. They expect fiscal balances to recover, reflecting macroeconomic and financial sector policies. Their projections are based on baseline data provided by IMF (2009b) and on the authorities' policy intentions as stated in the EU Pre-Accession Program document. As a second step, they look at potential changes for those projection in the event of downside risks materializing. In particular, the authors explore the impact on fiscal balances and government debt produced by two scenarios: lower growth in 2009 – 2011and prolonged stagnation. The approach used in this chapter goes in a quite different direction since it starts from a micro level (with assumptions and regulatory requirements for single banks) in order to assess the impact of bank failures on public finances.

The financial stability report produced by the Bank of England in 2010 performs one of the few quantitative analyses of the effectiveness of regulatory measures proposed to ensure the stable supply of financial services to the real economy. New regulatory requirements should be based on the analysis of the long-run costs and benefits: for this reason the authors propose a cost-benefit analysis of higher prudential capital levels for banks. The consequences of higher capitalisation in SYMBOL are represented by lower banks' systemic probabilities of default. The Bank of England concludes that higher capitalisation can produce higher or lower expected GDP according to whether the associated benefits (lower expected costs linked to banking crises) or costs (higher costs of credit leading to lower investments) are considered.

2.3 Methodology

The aim of this contribution is to evaluate the potential impact of banking crises on public finances. The SYMBOL model was therefore chosen to estimate the size of losses due to (simulated) bank defaults. Subsequently, losses are compared with the resources of the safety net in order to gain an idea of the amount of bank losses that has to be covered by public finances. This comparison is conducted on five scenarios resulting from the combination of four factors: capital requirements, the existence of deposit guarantee schemes and/or a resolution fund, bail-in arrangements, and contagion effects between banks.

This section is divided into two subsections, one describing the SYMBOL model used to generate the distribution of aggregate losses per country and the other assessing the role of financial safety net tools and the coverage of losses by public finances.

2.3.1 The SYMBOL model

The SYMBOL model, described in De Lisa et al. (2010), has been developed by the European Commission's Joint Research Centre in cooperation with its Directorate-General for the Internal Market and Services and experts on banking and regulation. The model is currently used by the Commission to evaluate the impact of new regulatory tools in banks' prudential regulations. In particular, it has been used to address issues in connection with the following:

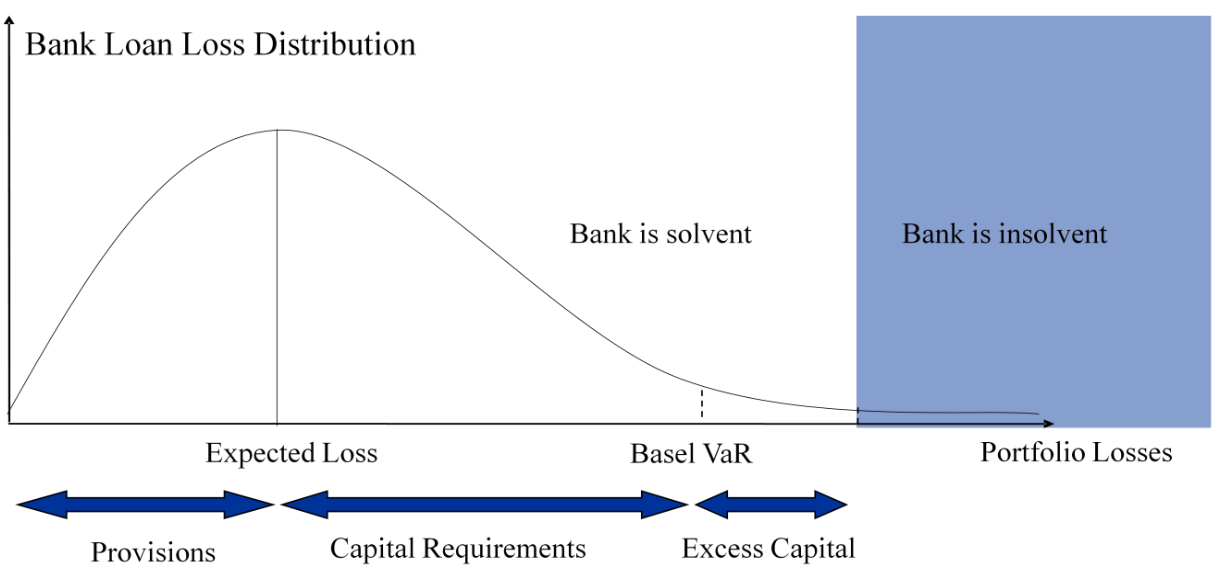
- reinforcement of deposit guarantee schemes by broadening their coverage and, as a consequence, increasing their funding;
- introduction of a resolution fund for banks in a proposal for a Directive on crisis management and bank resolution management;
- introduction of a European tax on financial activities (financial activities tax or financial transaction tax);
- drafting of a proposal for a new Capital Requirements Directive (CRD IV), aimed at adopting the new rules proposed in the Basel III accord (new definition of regulatory capital, new set of capital requirements for Tier 1 and total capital as a proportion of risk-weighted assets and introduction of a capital conservation buffer of 2.5% of risk-weighted assets);

- preparation of the annual report Public Finance in EMU, European Commission (2011).

As explained in De Lisa et al. (2010), SYMBOL was originally developed in order to extend the literature on deposit insurance schemes (now deposit guarantee schemes or DGSs). The few studies that have tried to estimate deposit insurance (see Sironi and Zazzara, 2004; Kuritzkes et al., 2005) relied on structural credit risk models and market data to derive banks' default probabilities, and then estimated the losses for the DGS in the event of bank failures. The model proposes a new way to estimate the DGS loss distribution that explicitly considers the link between deposit insurance and the regulatory framework introduced by Basel II.

The general idea of the model is that a bank goes bankrupt if its losses are higher that its total capital. Looking at the figure below, this happens whenever portfolio losses exceed the amount covered by provisions, capital requirements and excess capital that a bank holds in addition to what is required by regulation.

Figure 2.2: *Individual bank loss distribution*



The figure above plots the probability of occurrence of bank loan losses (measured on the vertical axis) against the size of the losses (measured on the horizontal axis). The distribution is skewed to the right: losses that are closer to the mean and median loss exhibit a higher probability of occurrence than extreme losses.

More specifically, the SYMBOL model performs the following steps:

- it estimates the average probability of default of the assets of any individual bank using the Basel II FIRB (Foundation Internal Rating Based) loss distribution function;
- it generates via Monte Carlo a sample of correlated bank asset losses;
- it checks banks' failures by comparing losses and capital levels;
- it estimates the distribution of aggregate (systemic) losses by country.

Looking at the characteristics of SYMBOL, the model can be said to initially take a micro approach, looking at losses and actual capital at individual bank level. The estimation of aggregate losses drives results toward a macro level, represented by the assessment of the severity of simulated banking crises through the comparison of losses and prudential regulation tools.

Estimating the average probability of default of the assets of any individual bank j[6]

This subsection describes the first step performed by the SYMBOL model, which is to obtain the default probabilities of the assets of individual banks from publicly available information on their accounts and on the regulatory framework. As stated earlier, SYMBOL is consistent with the regulatory framework set in place by Basel II as it makes explicit use of the Basel II FIRB formula for calculating capital requirements for credit risk *associated with a single exposure:*

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[6] Details about the Basel II IRB approach are taken from the BIS explanatory note (2005).

$$K = \left[LGD * N\left[\frac{1}{\sqrt{1-R}} N^{-1}(PD) + \sqrt{\frac{R}{1-R}} N^{-1}(0.999) \right] - PD * LGD \right] * MaturityAdjustments$$

As explained in the BIS explanatory note (2005), in June 2004 the Basel Committee issued a Revised Framework on International Convergence of Capital Measurement and Capital Standards that takes account of new developments in the measurement and management of banking risks for those banks that move to the 'internal rating-based' (IRB) approach.

As explained in Dierik et al. (2005), the internal rating based approach allows banks themselves to determine certain key elements in the calculation of their capital requirements. Its theoretical basis is the asymptotic single risk factor (ASRF) model for credit risk because it is portfolio invariant (i.e. the capital required for any loan only depends on the risk of that loan and not on the portfolio it is added to). Under the IRB approach, the required capital is based on the probability distribution of losses due to the default risk in a portfolio of loans or other financial instruments. The horizon of the risk assessment is set at one year and the confidence level is assumed equal to 99.9%.

The input parameters to the supervisory risk weight function are the following:

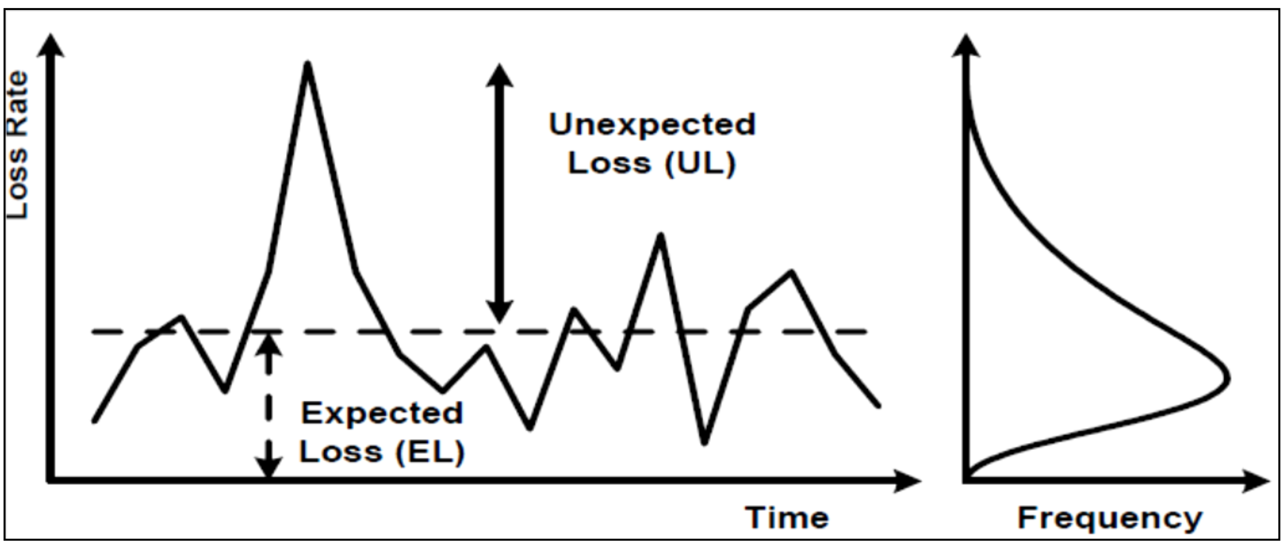
- Probability of Default (PD): it represents the average percentage of obligors that default in the course of one year in a specific rating grade;
- Loss Given Default (LGD): it gives the percentage of exposure the bank might lose in case the borrower defaults (expressed as percentage of the debt's original nominal value);
- Exposure at Default (EAD): it is an estimate of the amount outstanding in case the borrower defaults;
- Maturity (M): it represents the effective maturity of the loan.

A foundation and an advanced version of the IRB approach is available. Both approaches rely on bank's PD estimates, but only institutions using the advanced IRB approach are also permitted to rely on their own estimates of loss given default (LGD), exposure at default (EAD) and maturity (M).

The FIRB formula for capital requirements starts from the recognition of the loss-absorbing function associated to the capital that a bank holds.

A bank usually faces expected and unexpected losses: expected loss (EL) represents the forecasted average level of credit losses that a bank can reasonably expect to experience, whereas unexpected loss (UL) is the peak loss above the expected levels, as shown in the following figure.

Figure 2.3: *Distribution of losses for a bank derived by variation of losses over time*

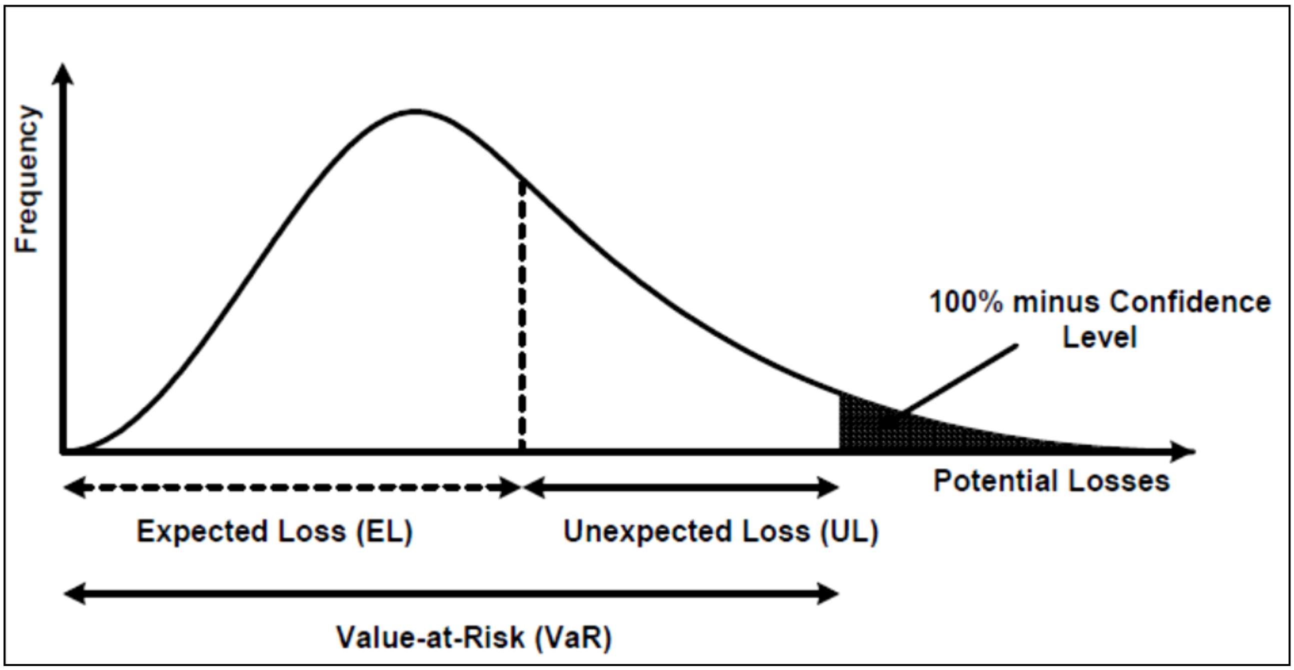


Source: BIS explanatory note on the Basel II IRB risk weight functions (2005)

Banks have an incentive to minimise the capital they hold in order to have economic resources that can be directed to profitable investments. On the other hand, since capital has a loss-absorbing function, the less capital a bank holds, the greater the likelihood that it will not be able to meet its own debt obligations.

The FIRB approach used by Basel II to determine the amount of capital a bank should hold focuses on the frequency of bank insolvencies arising from credit losses that supervisors are willing to accept. By means of stochastic credit portfolio models, it is possible to estimate the amount of loss that will be exceeded with a small, pre-defined probability defined as the probability of bank insolvency. The figure below represents the likelihood of losses of a certain magnitude.

Figure 2.4: *Likelihood of losses*



Source: BIS explanatory note on the Basel II IRB risk weight functions (2005)

Under Basel II the capital requirement K is expected to allow banks to cover their capital losses in at least 99.9 % of cases (confidence level represented in Figure 2.4).

The EL is assumed to be equal to the proportion of obligors that might default within a given timeframe (one year in the Basel context) multiplied by the outstanding exposure at default, multiplied by the percentage of exposure that will not be recovered. In other words:

$$EL = PD * EAD * LGD$$

These losses are usually shown as a percentage of EAD, so that EL can also be written as:

$$EL = PD * LGD$$

Basel II assumes a Merton-type (1974) one-factor model for credit risk, which assumes that obligors default if they cannot completely meet their obligations at a fixed assessment horizon because the value of their assets is lower than the due amount. Merton described the change in value of the borrower *i*'s assets as a normally distributed random variable that we can call X_i. Thus, the borrower defaults if X_i falls below a certain threshold L, represented by the obligor's liabilities. Since the value of the borrower is normally distributed, default occurs when

$$X_i \leq L_i = N^{-1}(PD)$$

Vasicek (2002) extended the Merton model with the introduction of dependence on a common factor in the driving process of X_i when considering a portfolio of N borrowers. The simplest assumption is a single correlation coefficient R for all the borrowers in the portfolio and a single normally distributed common factor. In this way each asset value can be seen as being driven by a common (systemic) factor C (that represents general economic conditions) and an idiosyncratic factor ε_i.

$$X_i = \sqrt{R}C + \sqrt{1-R}\varepsilon_i$$

C and ε_i are assumed to be independent and normally distributed.

R represents the correlation between each asset X_i and the systemic factor and, in the FIRB framework, it is defined as

$$R = 0.12 * \frac{1-\exp(-50 * PD_i)}{1-\exp(-50)} + 0.24 * \left(1 - \frac{1-\exp(-50 * PD_i)}{1-\exp(-50)}\right) - 0.04 * \left(1 - \frac{S_i - 5}{45}\right),$$

As you can see from the above formula, R decreases with increasing PDs and it increases with firm size (S_i).

Given the above specifications, the default condition becomes

$$X_i = \sqrt{R}C + \sqrt{1-R}\varepsilon_i \le L_i = N^{-1}(PD)$$

The stressed PD, called PD*, is computed by considering the distribution of X_i when the systemic factor is not average ($C \neq 0$). In other words

$$PD^{*} = P\left(X_i < L \middle| C\right) = P\left(\sqrt{R}C + \sqrt{1-R}\varepsilon_i < L \middle| C\right)$$

Replacing *L* with N^{-1}(PD) we obtain

$$PD^{*} = P\left(\sqrt{R}C + \sqrt{1-R}\varepsilon_i < N^{-1}(PD)\right)$$

Isolating the idiosyncratic factor:

$$PD^{*} = P\left[\varepsilon_i < \frac{N^{-1}(PD) - \sqrt{R}C)}{\sqrt{1-R}}\right]$$

Moreover, recalling that $P(\varepsilon_i < \alpha) = N(\alpha)$ the equation becomes

$$PD^{*} = N\left[\frac{N^{-1}(PD) - \sqrt{R}C}{\sqrt{1-R}}\right]$$

Capital requirements can be written as:

$$K \equiv StressedLoss - EL = PD^{*} * LGD - PD * LGD$$
$$K = LGD * N\left[\frac{N^{-1}(PD)}{\sqrt{1-R}} + \frac{\sqrt{R}C}{\sqrt{1-R}}\right] - PD * LGD$$

Recall that C is assumed not to be average. In particular, under the Basel II framework, C is meant to reflect a stressed scenario at 99.9% confidence interval. Thus, since C is normally distributed, it is possible to write $C = N^{-1}(0.999)$. Rewriting the above equation for K we obtain:

$$K = LGD * N\left[\frac{1}{\sqrt{1-R}} N^{-1}(PD) + \sqrt{\frac{R}{1-R}} N^{-1}(0.999)\right] - PD * LGD$$

That is the main part of the Basel II formula for capital requirements. Introducing the maturity adjustments, the above formula for single exposures becomes what is called the FIRB formula:

$$K = \left[LGD * N\left[\frac{1}{\sqrt{1-R}} N^{-1}(PD) + \sqrt{\frac{R}{1-R}} N^{-1}(0.999)\right] - PD * LGD\right] * (1 - 1.5B)^{-1} * [1 + (M - 2.5)B]1.06$$

where M is the time to maturity and B is a smoothed regression maturity adjustment defined as $B = [0.11852 - 0.05478 ln(PD)]^2$.

Maturity adjustments are needed because credit portfolios consist of instruments with different maturities. These adjustments are derived by applying a specific mark-to-market credit risk model, similar to the KMV Portfolio Manager™, in a manner consistent with Basel. The output of the KMV Portfolio Manager™ is a grid of Value at Risk (VaR) measures for ranges of rating grades and maturities. Maturity adjustments are the ratios of each of these VaR to the VaR of a standard maturity, which was set at 2.5 years. Furthermore, the grid of relative VaR figures (in relation to 2.5 years maturity) was smoothed by a statistical regression model.[7]

Given the assumption of infinite granularity, the overall capital requirement for a bank j is computed as the sum of the capital allocation parameter (K) of each exposure l multiplied by its amount A_l:

$$K_j = \sum_l K(PD_l)A_l \Rightarrow K = \frac{K_j}{\sum_l A_l}$$

SYMBOL estimates a proxy for the quality of a bank obligor portfolio (average PD of a bank's asset portfolio) by inverting the FIRB formula for K. This is possible because the actual capital requirement is known (when not directly quantified in the financial report it can be proxied as the 8% of risk weighted assets) and the other variables (LGD, M and S) are set at their regulatory values (LGD = 0.45; M = 2.5; S = 50): thus PD is the only unknown variable in the FIRB formula above.

The average probability of default computed for each bank j is called implied obligor PD.

[7] Details about the regression function can be found in the BIS explanatory note (2005).

Generating via Monte Carlo a sample of loan losses

At this point, the average probability of default of the credit portfolio of each bank is estimated.

Individual banks' losses can be simulated on the basis of the estimated average implied probability of default of each bank's obligors and the shape of the distribution of losses assumed in the Basel FIRB approach.

Individual default probabilities of banks cannot be computed independently from the default probabilities of other individual banks: the probability of default of each bank depends — via the interbank market — on the probability that other banks fail. The only case where this does not hold is where there is no contagion effect between banks.

Starting from the estimates of the average probability of default, SYMBOL generates for each bank j $(j = 1,\dots,k)$ credit losses via MC simulations based on

$$L_{ij} = LGD * N\left[\sqrt{\frac{1}{1-R}}N^{-1}\left(\overline{PD}_j\right) + \sqrt{\frac{R}{1-R}}N^{-1}\left(z_{ij}\right)\right] - \overline{PD}_j * LGD$$

where $i = 1,\dots,n$ refers to the simulation, $N(z_{ij}) \sim N(0,1)$ for every i,j and $Cov(z_{ij},z_{ik}) = 0.5$ for every $j \neq k$. In particular, a sample of losses L_{ij} is generated via random shock for $N^{-1}(z_{ij})$. The procedure allows to obtain a $(n \times k)$ matrix of losses.

As can be seen from the hypothesis about covariance, the model takes into account a first source of systemic risk that derives from the fact that banks have correlated exposures. As explained in De Lisa et al. (2010), correlation exists as a consequence of banks' common exposure either to the same borrower or, more generally, to a particular common influence of the business cycle. The model assumes that banks share the same value of asset correlation, equal to 0.5. This value has been chosen referring to Sironi and Zazzara (2004), who find that the average asset correlation for a sample of Italian banks is around 50 %.

Checking which bank fails

Banks' simulated losses are then compared with banks' capital: whenever losses exceed capital, banks are considered to default. In particular, defaults occur whenever the amount of losses is higher than the amount of provisions (or expected losses) plus the amount of capital required by regulation (*K*) plus the excess capital.[8] In doing this, the procedure generates a (n x k) matrix of zeros (no failure of bank j in simulation n) and ones (failure).

Estimating the distribution of aggregate losses

Individual banks' excess losses (i.e. losses exceeding banks' total capital) are combined to gain an estimation of the overall aggregate bank excess losses for a given country. Losses are then divided by the sample size to obtain the aggregate loss distribution for the entire bank population of a country. The probability distribution of aggregate losses is computed under two possible conditions: 'contagion' and 'no contagion'.

As explained by De Bandt et al. (2009), contagion is one of the materialisations of systemic risk. Contagion results in turn from two risks: first, the trigger event, that is the risk that at least one component of the system could default (probability of a bank defaulting) and, second, the risk that this shock could propagate through the system (potential impact of the default). As the former can stem from a variety of unexpected situations, and is driven mainly by the riskiness and solvency of assets, SYMBOL focuses on the latter. SYMBOL takes into account one of the channels of contagion: the interbank market.

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[8] See Figure 2.2 for the identification of the solvency and insolvency areas.

In the 'no contagion' case, banks are considered to default in an orderly manner without possibly creating contagion with the other banks to which they are connected via the interbank market. In contrast, in the 'contagion' case, domino effects generated via the interbank market are taken into account[9]. More specifically, whenever a bank defaults, it is assumed that 40 % of its losses are passed to the remaining banks via a proportionality criterion. If bank *j* fails, it is assumed that 40 % of its losses are passed to the remaining banks according to the weight of the credit share of remaining banks in the interbank market. For instance, considering bank *h* as one of the remaining banks after the failure of bank *j*. The (interbank) losses incurred by bank *h* can be written as:

$$IBloss_h(j) = IB_j^- \frac{IB_h^+}{\sum_{k \neq j} IB_k^+}$$

where IB^- and IB^+ are, respectively, the debt exposure and the credit exposure in the interbank market. The total loss of bank *h* due to interbank exposures is given by

$$IBloss_h = \sum_j IB_j^- \frac{IB_h^+}{\sum_{k \neq j} IB_k^+}$$

Therefore, the total loss suffered by each bank is given by the sum of the losses on its loan portfolio and the losses directly linked to interbank exposures.

[9] Only domestic exposures are considered in contagion effects.

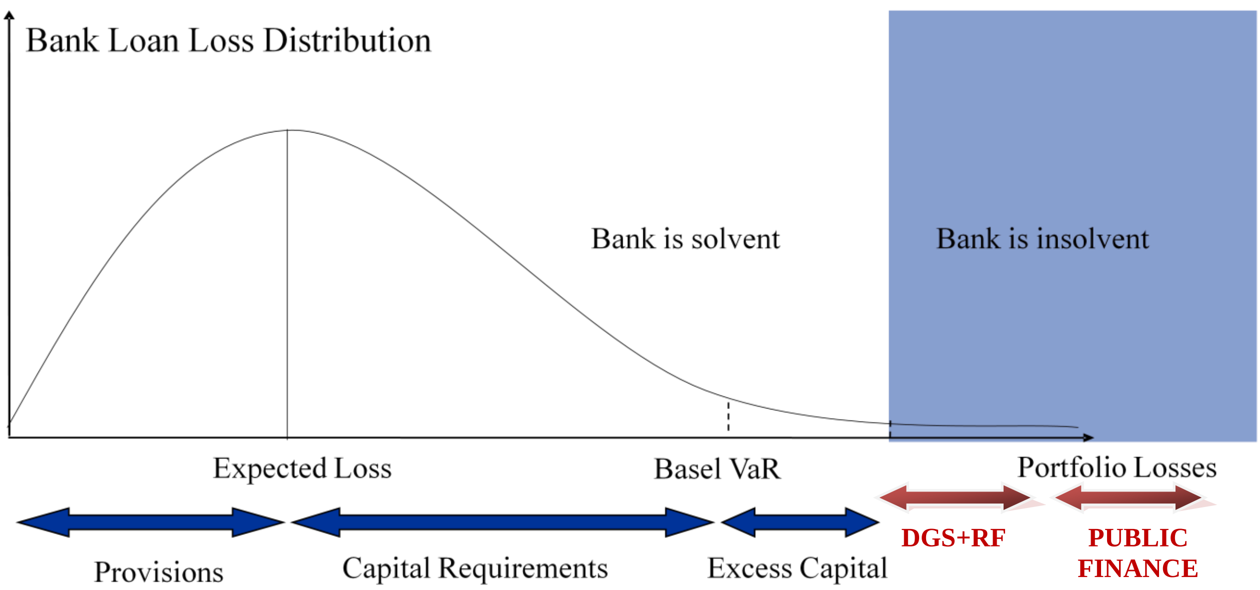
Considering interconnections between financial institutions, SYMBOL is able to capture the severity of the impact of systemic risk on the overall economy that goes beyond the correlation of banks' assets.

In modelling contagion, there are two fundamental assumptions: the quantity of losses that are passed to the other banks via the interbank market and the construction of the matrix containing interbank exposures. Regarding the first point, as previously stated SYMBOL assumes that in the event of failure, 40 % of losses are passed to the other banks. This is in line with the upper bound of economic research on this issue (see James, 1991; Mistrulli, 2007; Upper and Worms, 2004). Concerning the interbank matrix, SYMBOL assumes that each bank is connected to all the other banks operating in its country with a proportionality criterion associated with the proportion of credit exposure in the interbank market. This means that SYMBOL assumes maximum entropy in the interbank market, which is equivalent to saying that there is maximum dispersion of interbank linkages. Uncertainty tests have been conducted on this point (see the next chapter of this work), and they demonstrate that SYMBOL results are not significantly affected by this hypothesis.

2.3.2 The impact of aggregate bank losses on public finances

Once the aggregate bank loss estimates are obtained, it is possible to estimate the potential risk for public finances deriving from defaults in the banking sector. This subsection explains how such an estimation is conducted. Losses generated in the banking sector are assumed here to be firstly covered by banks' capital and, when this is insufficient, by the various tools forming part of the regulatory financial safety net. It is then assumed that losses that cannot be absorbed by these instruments are covered by the government balances, where possible, as has occurred in the current financial crisis.

Figure 2.5: *Individual bank loss distribution. A closer look at financial safety net tools*



Financial safety net tools are deposit guarantee schemes (DGSs) and bank resolution funds (RFs): as can be seen from the above figure, they work progressively as barriers to absorb bank losses. The assumption made here is that when losses materialise, they are first covered with the bank's capital (provisions, capital requirements and excess capital, if any). If this capital is not sufficient, the bank defaults and DGSs and RFs are supposed to intervene to ensure, respectively, that covered depositors are unaffected and that the defaulting bank is wound down in an orderly fashion in order to prevent contagion effects. If funds are still not sufficient to absorb the losses, then these pass through to the public finances. DGSs are the element of the financial safety net designed to offer protection to covered depositors and, as a consequence, to support the stability of the entire economy. They ensure depositors that, in the event of a bank failure, they will be able to recover at least a proportion of their deposits.[10]

The establishment of RFs in the EU context is still under discussion. In a European Commission Communication (26/5/2010) on RFs, it clearly emerges that the Commission supports the establishment of *ex ante* resolution funds financed by a levy on banks to facilitate the resolution of failing banks in ways which avoid contagion, and allow the bank to be wound down in an orderly manner and in a timeframe that avoids the 'fire sale' of assets. The Commission believes that RFs are a necessary part of a new crisis management framework that seeks to eliminate the reliance on taxpayers' funds to bail out banks. The Commission highlights that an RF must not be used as an insurance against failure or to bail out failing banks, but rather to facilitate an orderly failure. Funds must be available for the resolution of banks irrespective of their size and interconnectedness and their funding should be provided by *ex ante* contributions from banks. Bank RFs should remain separate from the national budget and reserved exclusively for resolution costs. Examples of different measures that resolution funds might be expected to cover are provided below:

- financing a bridge bank to allow the continuation of operations for an insolvent institution;
- financing a total or partial transfer of assets and/or liabilities from the ailing entity to a third party;
- financing a good bank/bad bank split;
- covering administrative costs, legal and advisory fees.

Rules for the determination of funds available to DGSs and RFs are still under negotiation in the Council and Parliament. For this reason these computations are based on a simplified hypothesis in which the amount of funds available for DGSs and RFs is assumed to be the higher of 1.5% of

[10] For a detailed description of DGSs see the previous chapter 'Revision of risk-based contributions using CDS spreads: an application to the Italian banking system'.

covered deposits or 0.3 % of total non-equity liabilities of the banking system in any EU Member State. The total amount of the DGS and the RF in each of the countries considered is reported in the section on data.

The model is run under five different scenarios that represent five different effectiveness and regulatory settings. In particular, the following situations are explored:

- Regulatory capital requirement settings. Banks can be considered to meet Basel II requirements, which are satisfied by their 2009 capital without the need for recapitalisation, or they can be asked to recapitalise in order to meet new capital requirements introduced by Basel III and based on a stricter definition of risk-weighted assets and capital. In the second case, computations are taken from the European Banking Authority quantitative impact study and two different capital requirement settings are considered: in the first setting banks must hold a minimum capital requirement equal to 8 % of their risk-weighted assets; in the second one a minimum capital conservation buffer of 2.5 % is put on top, so as to reach a minimum capital requirement equal to 10.5 % of risk-weighted assets.
- DGS/RF. A DGS and an RF can be set up or not, so that part of the losses can or cannot be absorbed by these two entities.
- Bail-in/no bail-in. In the bail-in setting, bondholders and non-covered depositors are assumed to absorb bank losses outside the scope of intervention of the DGS/RF (DGSs cover eligible depositors up to € 100 000. Non-eligible depositors are, for example, pension funds, insurance companies, credit institutions). In the no bail-in case, DGSs and RFs are unable to discriminate: in this way they end up covering also bondholders and non-covered depositors.
- Contagion/no contagion. The effects of contagion via the interbank market are not considered as a quantity to be added to bank losses in the no contagion case.

Combining the above cases, five scenarios are considered:

Table 2.3: *Scenario definitions*

	Capital settings			DGS/RF		Bail-in		Contagion	
Scenario	**Basel II**	**Basel III 8 %**	**Basel III 10.5 %**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**
1	X				X		X	X	
2		X		X			X	X	
3		X		X			X		X
4		X		X		X			X
5			X	X		X			X

A brief description of the five scenarios is given below:

Scenario 1. This is the most risky scenario because banks are assumed to satisfy the less strict capital requirements laid down in Basel II. This represents the situation at the beginning of the current financial crisis. DGSs/RFs are ineffective in blocking contagion and they cover all losses (no bail-in).

Scenario 2 (current situation). In this scenario capital requirements are set at 8 % of risk-weighted assets as defined in Basel III. DGSs/RFs are ineffective in blocking contagion and they cover all losses.

Scenario 3 (the DGS/RF eliminates contagion). Banks must hold at least 8 % of risk-weighted assets as defined within Basel III. DGSs/RFs are effective in blocking contagion and they cover all losses without discriminating between covered and non-covered depositors.

Scenario 4 (introduction of bail-in). This scenario differs from the previous one only because of the bail-in condition. In this case DGSs/RFs do not intervene to cover all losses: bondholders and non-covered depositors are assumed to cover part of bank losses.

Scenario 5 (minimum conservation buffer). This is the least risky scenario, where banks are supposed to hold a minimum capital equal to 10.5 % of risk-weighted assets as defined in Basel III (conservation buffer).

The analysis of different scenarios is useful to understand the effectiveness of regulatory measures proposed to strengthen the financial safety net.

The following section provides details of the data used for simulations. The results section provides three sustainability indicators that measure, respectively, the probability for public finances of being hit by banking losses, the distribution of costs for public finances expressed as a percentage of GDP and the probability of becoming high-risk due to a banking crisis.

2.4 Data

The analysis was conducted on four banking systems featuring different bank concentration ratios and business models: Germany (DE), Ireland (IE), Portugal (PT) and Sweden (SE).

The main data source was Bankscope, a proprietary database of banks' financial statements produced by the private company Bureau van Dijk. The dataset has some drawbacks: it doesn't cover all the banks in EU countries, some variables are missing for some banks and it is not unusual to find some errors in values.

Where necessary and if possible, data were integrated with public information on banks' financial statements released by supervisory authorities and/or central banks. Among the Member States in the analysis, only Ireland provided the requested information. For the other countries, the Bankscope dataset was detailed enough to obtain a complete picture of the banking system.

Missing values were indirectly computed in the following ways:

- using (individual or group) banking ratios provided by Bankscope;
- by a residual method relying on available data;
- looking at individual banks' publicly available balance sheets;
- analysing national average values and estimations provided either by the European Central Bank or by the European Banking Authority.

Where missing values could not be derived from other sources, the corresponding bank was eliminated from the analysis.

Coherence among variables and data reliability were also investigated either using simple checks (for example, it is useful to verify that the amount of deposits plus capital is always smaller than or equal to total assets) or using ECB data.

Table 2.4 presents aggregate information on a selection of key variables for the samples of banks used in the simulations. The reference year is 2009. Financial statements relating to a given year are usually prepared at the end of the fiscal year, so the relevant data only become available in Bankscope around September of the following year. For this reason, the analysis used 2009 data, as the full set of 2010 data would only be available from the end of September 2011.

Table 2.4: *Description of the sample used for simulations*

	Number of banks	Sample % population	Capital (€m)	Total assets (€m)	Total liabilities (€m)
DE	1 482	64.19 %	232 711	4 648 331	4 415 620
IE	24	101.91 %	65 392	1 221 181	1 155 789
PT	14	66.49 %	26 341	323 762	297 421
SE	66	52.37 %	33 054	455 355	422 301

	Interbank debts (€m)	Interbank credits (€m)	Total covered deposits
DE	1 086 016	790 975	1 093 841
IE	276 738	148 729	147 145
PT	43 561	34 504	82 952
SE	97 604	122 872	75 383

	Capital/total assets	Interbank debts/total assets	Interbank credits/total assets	Herfindahl index (over total assets)
DE	0.050	0.234	0.170	0.114
IE	0.054	0.227	0.122	0.154
PT	0.081	0.135	0.107	0.259
SE	0.073	0.214	0.270	0.292

The second column of the table shows the coverage of the samples, expressed as the total assets of banks in the sample as a percentage of the estimated total assets of the entire population of banks in the Member State concerned. The latter is obtained from the 2010 ECB EU banking structures publication.[11]

Data coverage for the four countries presented here is satisfactory, since it is always above 50 %. Data used to construct the 'Sample % population' for Ireland are derived both from the ECB and from the Irish Central Bank: the imperfect coherence of data derived from the two sources makes it possible to obtain a sample population above 100 %.

Capitalisation levels, measured by the ratio capital/total assets, first approximate the extent to which banks are resilient to defaults of their own assets. We have to remember that such resilience also depends on the riskiness of the assets, which is taken into account in the scenario-generating process when the probability of default of the assets of each individual bank is computed.

Columns indicating interbank volumes represent the size of interbank debts and credits over total assets. Obviously, countries where interbank exposures have significant volumes compared to total assets are more exposed to a shock transmission occurring via the interbank channel. If we look at aggregate data reported above, we can see that Germany, Ireland and Portugal have intense interbank activity since interbank exposures account for a large share of total assets (compared to the same value associated with Sweden).

Table 2.4 also shows Herfindahl indices computed for total assets to monitor concentration in the banking system. The index is generally calculated as:

[11] Source: European Central Bank (2010), EU banking structures: http://www.ecb.int/pub/pdf/other/eubankingstructure201009en.pdf.

$$H = \sum_{j=1}^{J} s_j^2 ,$$

where s_j is the market share of firm k in the market with respect to the variable considered (total assets, interbank debts and credits).

Looking at the tables above, it is clear that the countries considered are heterogeneous. This is true not only in terms of interbank exposures, but also in terms of capitalisation and sample size.

Germany has the largest quantities, and this is justified by the high number of banks considered in the sample. Its capitalisation is the lowest among the four countries, whereas the level of interbank exposures (debts and credits) over total assets is among the largest. According to its Herfindahl index, it doesn't have a highly concentrated banking system in terms of total assets.

The Irish banking system is not highly concentrated and is made up of a small number of banks highly exposed in the interbank market. We expect that contagion effects will be more intense in Ireland because of the high incidence of interbank lending activity over total assets and capital.

Portugal has the smallest number of banks, a high level of capitalisation and the highest level of concentration in terms of total assets.

Sweden shows high capitalisation and large interbank exposures if compared to the amount of total assets. Moreover, its Herfindahl index over total assets indicates a high level of concentration.

Differences among countries in terms of input data will determine differences in results.

For example, the amount of a bank's capital represents the first barrier against losses. According to SYMBOL, a bank is considered to default whenever its capital is insufficient to cover losses. For this reason, a banking system composed of banks whose amount of capital exceeds capital requirements will be more resilient to shocks and, therefore, will experience a smaller number of failures.

Where there is contagion, SYMBOL assumes that 40 % of interbank debts are passed on as losses to creditor banks in the event of failure. Thus, the amount of interbank exposure will accelerate defaults that occur after the first one (in this dataset three out of four countries show large amounts of interbank debts and credits, also if compared to the amount of total assets).

The following table shows the amount of DGS/RF available for each country:

Table 2.5: *Total amount of funds available to the DGS and the RF*

	DGS+RF (€m)
DE	31 308
IE	3 423
PT	1 686
SE	2 510

Note: computations are based on ECB data on covered deposits and non-equity liabilities. Results are then rescaled to the size of the sample considered here.

Remember that DGSs and RFs are supposed to cover part of the losses deriving from defaults in order to protect depositors (DGSs) and block contagion effects (RFs).

2.5 Results

The following results are based on the number of simulations necessary to obtain, for each country, 100 000 runs with at least one default. This procedure is necessary in order to have a sufficiently populated right tail of the loss distribution and it requires running up to 2.3 million simulations.

Following the four steps explained in section 2.3.1, the average probability of default was first computed and then samples of correlated bank asset losses were simulated. Failures were identified and, for each country, the distribution of aggregate systemic losses with and without contagion was derived. The part based on MC simulations is run on a C compiled code that takes from a minimum of ten minutes to obtain results for samples with a small number of banks and a low level of capitalisation (Ireland in our case) to a maximum of about four hours to perform simulations for complex samples such as Germany.

With the distribution of aggregate losses it is possible to verify the intervention of DGSs/RFs (in those scenarios where DGSs/RFs are established) and to compute the amount of losses that is left uncovered and has to be managed with public finances. The entire procedure is run with three different capital requirements options (Basel II, Basel III 8%, Basel III 10.5%) and with and without the bail-in of non-covered depositors.

Three indicators of the potential impact of bank losses on public finances are presented here. Indicators represent three (complementary) approaches to evaluating banking systems and connected financial safety net tools in terms of their effectiveness in covering costs associated with a banking crisis.

Results in different scenarios will provide an overview of the plausible consequences of the existence of different regulatory frameworks. In addition, differences between the four countries are useful to better understand the entity of results.

The **first indicator** is the probability that public finances are hit by losses deriving from bank defaults. This probability is taken using the distribution of banking system losses. The five scenarios influence the definition of that probability in the following way:

- Scenario 1. Denoting by L^c the distribution of banking system losses with contagion under the setting considered (Basel II, DGS/RF not established, no bail-in), the probability that public finances are hit (PPF) is defined as:

$$PPF = P\left(L^C(BaselII) > 0\right)$$

- Scenario 2. In this scenario stricter definitions of capital and risk-weighted assets are provided by Basel III. The minimum capital requirement is set at 8 % of those risk-weighted assets, DGSs and RFs are established and there is no bail-in. PPF is thus defined as:

$$PPF = P\left(L^{C}(BaselIII, 8\%) - Loss(DGS/RF) > 0\right)$$

where Loss(DGS/RF) defines the amount of losses that is absorbed by funds available to the DGSs/RFs.

- Scenario 3. In this scenario the presence of DGSs/RFs becomes effective in blocking contagion, thus the amount of losses that is important to compute PPF is L^{nc} (losses without contagion):

$$PPF = P\left(L^{nc}(BaselIII, 8\%) - Loss(DGS/RF) > 0\right)$$

- Scenario 4. Part of the losses is here absorbed by bondholders and non-covered depositors. In this way the quantity of losses L^{nc} that has to be covered must be diminished by the percentage of losses absorbed by those stakeholders.

$$PPF = P\left(L^{nc}(BaselIII, 8\%)\alpha - Loss(DGS/RF) > 0\right)$$

$$\alpha = \frac{CovDep + InterbankDebts}{TotLiabilities}$$

α represents the share of liabilities that DGSs/RFs are responsible for.

- Scenario 5. This scenario differs from the previous one because it considers a minimum capital conservation buffer. PPF is now defined as

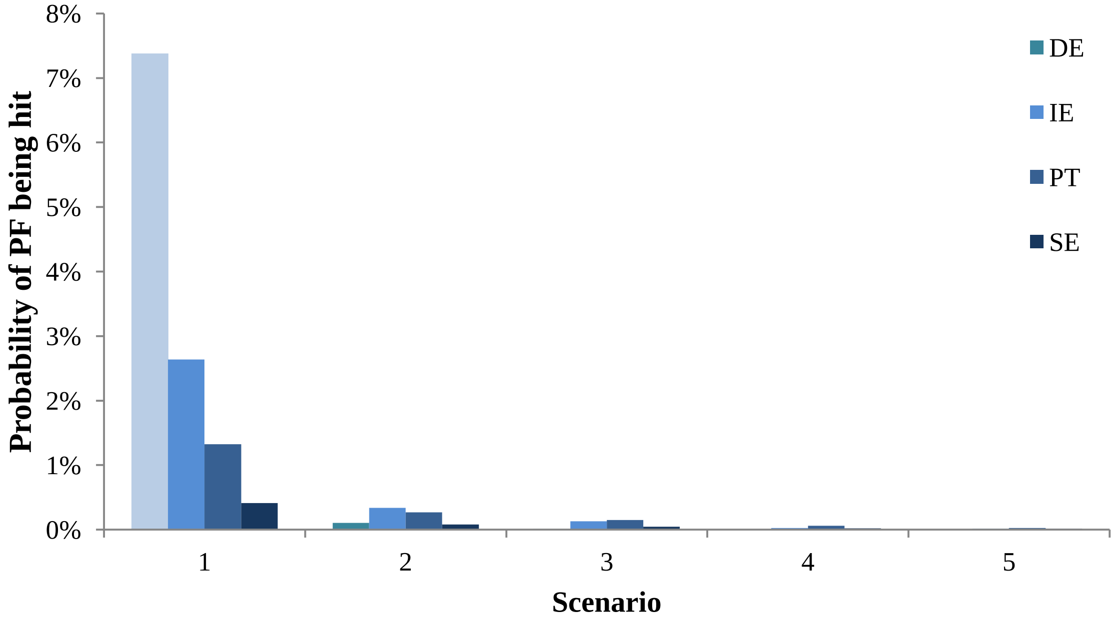
$$PPF = P\left(L^{nc}(BaselIII, 10.5\%)\alpha - Loss(DGS / RF) > 0\right)$$

α is defined as in Scenario 4.

Table 2.6: *Probability that public finances are hit by bank defaults in different scenarios*

	Scenario 1	**Scenario 2**	**Scenario 3**	**Scenario 4**	**Scenario 5**
DE	7.381 %	0.1068 %	0.0118 %	0.0028 %	0.0025 %
IE	2.639 %	0.3363 %	0.1314 %	0.0265 %	0.0136 %
PT	1.324 %	0.2685 %	0.1470 %	0.0599 %	0.0260 %
SE	0.412 %	0.0795 %	0.0444 %	0.0202 %	0.0158 %

Figure 2.6: *Probability that public finances are hit by bank defaults in different scenarios*



The table and figure above clearly demonstrate the decreasing riskiness of the five scenarios. In Scenario 1 (previous regulatory situation), Germany shows a relatively high (7.381 %) probability of its public finances being hit by losses generated by bank defaults. Ireland and Portugal are associated with a relatively high probability both in Scenario 1 and in Scenario 2 (current regulatory situation). The probability associated with Sweden is always below 0.5 %.

This indicator does not, however, yield much information on the size of the losses that might hit the public finances and reflects the cases of relatively small losses from minor defaults in the banking sector.

For this reason, a **second indicator** that looks at the size of losses is provided. It represents the distribution of costs for public finances expressed as a percentage of the 2009 GDP of each country.

The table below represents selected percentiles of the probability distribution of the costs for government finances, starting from the last decile. Data are presented as a percentage of GDP (as of 2009). In the estimation of costs, the distribution of banking system losses is rescaled on the basis of the size of the sample employed, as expressed in Table 2.4 in section 2.4.

Table 2.7: *Selected percentiles of the distribution of losses hitting public finances (% of GDP)*

DE	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
90	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
95	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
97	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
99	0.02 %	0.00 %	0.00 %	0.00 %	0.00 %
99.25	0.03 %	0.00 %	0.00 %	0.00 %	0.00 %
99.5	0.06 %	0.00 %	0.00 %	0.00 %	0.00 %
99.75	0.13 %	0.00 %	0.00 %	0.00 %	0.00 %
99.9	13.55 %	12.09 %	0.00 %	0.00 %	0.00 %
99.925	14.97 %	13.49 %	0.00 %	0.00 %	0.00 %
99.95	16.36 %	14.92 %	0.00 %	0.00 %	0.00 %
99.975	17.90 %	16.46 %	0.00 %	0.00 %	0.00 %
99.99	19.50 %	18.08 %	0.12 %	0.00 %	0.00 %
99.995	20.76 %	19.34 %	0.74 %	0.00 %	0.00 %
99.999	24.05 %	22.71 %	2.81 %	0.71 %	0.76 %

IE	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
90	0.00%	0.00%	0.00%	0.00%	0.00%
95	0.00%	0.00%	0.00%	0.00%	0.00%
97	0.00%	0.00%	0.00%	0.00%	0.00%
99	42.77%	0.00%	0.00%	0.00%	0.00%
99.25	45.09%	0.00%	0.00%	0.00%	0.00%
99.5	47.73%	0.00%	0.00%	0.00%	0.00%
99.75	52.20%	3.38%	0.00%	0.00%	0.00%
99.9	56.53%	**40.98%**	0.54%	0.00%	0.00%
99.925	57.94%	43.25%	1.15%	0.00%	0.00%
99.95	59.92%	46.30%	2.09%	0.00%	0.00%
99.975	63.25%	50.60%	3.91%	0.05%	0.00%
99.99	67.97%	55.45%	6.59%	1.02%	0.29%
99.995	71.66%	59.22%	9.09%	1.93%	1.14%
99.999	81.95%	69.24%	15.65%	4.31%	3.38%

PT	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
90	0.00%	0.00%	0.00%	0.00%	0.00%
95	0.00%	0.00%	0.00%	0.00%	0.00%
97	0.00%	0.00%	0.00%	0.00%	0.00%
99	0.01%	0.00%	0.00%	0.00%	0.00%
99.25	0.04%	0.00%	0.00%	0.00%	0.00%
99.5	0.68%	0.00%	0.00%	0.00%	0.00%
99.75	3.24%	0.59%	0.00%	0.00%	0.00%
99.9	8.55%	3.12%	0.59%	0.00%	0.00%
99.925	9.95%	4.39%	1.06%	0.00%	0.00%
99.95	11.56%	6.72%	1.76%	0.14%	0.00%
99.975	13.83%	9.81%	3.03%	0.66%	0.03%
99.99	16.66%	12.94%	4.86%	1.42%	0.72%
99.995	19.06%	15.52%	6.44%	2.07%	1.32%
99.999	24.95%	21.60%	10.51%	3.75%	2.93%

SE	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
90	0.00%	0.00%	0.00%	0.00%	0.00%
95	0.00%	0.00%	0.00%	0.00%	0.00%
97	0.00%	0.00%	0.00%	0.00%	0.00%
99	0.00%	0.00%	0.00%	0.00%	0.00%
99.25	0.00%	0.00%	0.00%	0.00%	0.00%
99.5	0.00%	0.00%	0.00%	0.00%	0.00%
99.75	0.00%	0.00%	0.00%	0.00%	0.00%
99.9	0.02%	0.00%	0.00%	0.00%	0.00%
99.925	2.27%	1.41%	0.00%	0.00%	0.00%
99.95	3.34%	2.48%	0.00%	0.00%	0.00%

99.975	5.49 %	4.64 %	0.91 %	0.00 %	0.00 %
99.99	19.93 %	19.08 %	2.55 %	0.52 %	0.35 %
99.995	22.23 %	21.37 %	3.96 %	1.08 %	0.88 %
99.999	27.22 %	26.36 %	7.74 %	2.60 %	2.37 %

The following table contains data about GDP in 2009.

Table 2.8: *GDP 2009*

	GDP (€m)
DE	2 397 100
IE	159 646
PT	168 076
SE	292 682

Table 2.7 can be read in the following way: in the current regulatory situation (as modelled by Scenario 2) with a given probability, such as 0.1 % (line 99.9 in the table), Ireland would be exposed to a heavy burden on its public finances equal to 40.98 % of GDP (in bold in the table). A default rate equal to 0.1 % corresponds to a rating class between A^- and BBB^+ in the Standard & Poor's classification.

Comparing across countries requires caution: for example, the expected loss cannot be read as an indication of the riskiness of the country because countries with a better regulatory system will tend to have higher average losses. Indeed, a good regulatory system will cover small losses (which happen with much higher probability) and will only leave big losses, thus increasing the average loss. The comparisons of values at the same percentile are correct.

Once again, the decreasing riskiness of the five scenarios is evident looking at results within individual countries. Moreover, the effects of contagion can be quantified looking at differences between Scenarios 2 and 3, which differ only because of the introduction of contagion (Scenario 2 is with contagion). As expected, all four countries exhibit higher costs for public finances in the event of contagion. The magnitude of such differences depends on specific characteristics associated with each country (and, in particular, on interbank exposures).

A **third sustainability indicator** is the probability that, due to a banking crisis hitting public finances, a Member State becomes high-risk in terms of the sustainability indicator S2 presented in the sustainability report proposed by DG ECFIN in 2009. As explained in the report, the concept of sustainability of public finances concerns the ability of a government to finance its current debt and expected expenditure through future revenues. Sustainability is thus a long-term concept that can be addressed using alternative approaches. Indicators of sustainability generally assume the continuation of current revenue and expenditure policies over a finite or infinite timescale, usually taking the expected development of population size and structure into account. More specifically, these indicators reflect the projected development of main tax revenues (direct and indirect taxes and social contributions) and expenditure (pensions, health care, long-term care, etc.) under current policy over a very long horizon. In particular, the S2 indicator shows the adjustment to the current primary balance required to fulfil the infinite horizon intertemporal budget constraint, including paying for any additional expenditure arising from an ageing population. It quantifies the gap that must be closed to ensure the sustainability of public finances. The larger the value of the gap, the greater the necessary adjustment to the structural primary balance to ensure sustainability. Obviously S2 does not provide any guide as to how the adjustment should take place.

S2 is composed of two parts: the first one is the required adjustment given the initial budgetary position, the second one represents the required adjustment due to long-term changes in the primary balance.

Regarding the first part, the public finances of a given country may be unsustainable if the initial structural primary balance and the projected interest payments and economic growth imply an ever-increasing debt ratio. Thus, the first component corresponds to the gap between the initial structural primary balance and the debt-stabilising primary surplus.

The second component is the additional adjustment required as a result of government expenditure either to 2060 or over an infinite horizon. The magnitude of this component depends on both the demographic outlook for countries and their social protection arrangements. This component represents either the change required to pay for additional expenditure or the size of a structural reform to social protection schemes to avoid the increase that would otherwise ensue.

The third indicator presented here corresponds to the probability that S2 exceeds 6 %. As a first approximation it is assumed that all costs due to losses in the banking system are paid by the Member State in the current year, thus increasing the primary deficit by a corresponding amount.[12]

The following table presents the results for the four Member States under consideration.

Table 2.9: *Probability of becoming high-risk due to a banking crisis in terms of the sustainability indicator S2*

	Probability S2 > 6 %					**6-S2 (% of GDP)**
	Scenario 1	**Scenario 2**	**Scenario 3**	**Scenario 4**	**Scenario 5**	
DE	0.110 %	0.110 %	0.001 %	0.0001 %	0.0001 %	1.80 %
IE	n/a	n/a	n/a	n/a	n/a	-9.00 %
PT	0.490 %	0.250 %	0.090 %	0.022 %	0.010 %	0.50 %
SE	0.019 %	0.018 %	0.0009 %	0.000008 %	0.000008 %	4.20 %

Once again it is clear that the five scenarios represent five different levels of risk. In Scenario 1 and Scenario 2, Germany and Portugal exhibit a relatively high probability of becoming high-risk in terms of S2. Sweden emerges as a relatively safe country as far as the risks to public finances coming from the banking sector are concerned.

Data about Ireland are expressed as *n/a* since the country experienced a deficit higher than 6 % of GDP in 2009.

[12] Potential impacts on interest on the government debt might also be included.

The results presented above are intended to represent a new approach to addressing the costs of financial crises. SYMBOL can be used to simulate troubles in banking systems considering different regulatory settings: the three indicators of sustainability are only an example of the conclusions that can be reached using its simulations.

2.6 Conclusions

In this chapter I have focused on public finances and their risk of being hit by losses deriving from banking crises. In the current financial crisis, the strong link between banks and governments emerges clearly: on the one hand, banks are highly exposed toward the public sector since government bonds are used by banks as collateral to obtain liquidity. On the other hand, government assistance to the banking sector has been sizeable during the current crisis as well as in past events.

Quantifying the effects that a banking system in trouble could have on the stability of government finances is of crucial importance. Past literature includes scientific contributions that have tried to summarise the characteristics of past banking crises, in order to find common features that could be used to interpret the current situation in banking systems. Nevertheless, no one has tried to forecast the impact that (systemic) banking crises could have on governments' finances, with the only exception being the Bank of England's assessment of costs/benefits associated with the introduction of higher capital levels. In this chapter I propose an application of the SYMBOL model developed by De Lisa et al. (2010): after computing an average probability of default obtained by inverting the Basel FIRB formula, it uses MC simulations to generate banks' losses and it computes the aggregate losses by country. Aggregate losses are analysed under five scenarios that include different regulatory settings. In this way SYMBOL makes it possible to forecast the impact of losses on public finances taking into consideration changes in the definition of capital requirements (Basel II; Basel III with the minimum capital requirement expressed as 8% of the — new — risk-weighted assets, Basel III with the minimum capital conservation buffer), changes relating to financial safety net tools (DGS and RF, bail-in) and the existence of contagion between banks.

Results are presented in terms of three sustainability indicators: the probability that public finances are hit by bank defaults, the distribution of losses hitting public finances (expressed as a percentage of GDP) and the probability that, due to a banking crisis hitting public finances, a Member State becomes high-risk in terms of the sustainability indicator S2.

It emerges that the five scenarios presented correspond to different levels of riskiness. Contagion plays a crucial role in the quantification of losses hitting public finances (look at the comparison between Scenario 2 and Scenario 3) and, in terms of a comparison between countries, Sweden seems a relatively safe country.

This chapter is intended as a starting point for assessing risks to public finances as well as for evaluating the soundness of the financial safety net. In particular, the introduction of different regulatory settings can be evaluated by analysing their capacity to absorb losses generated by systemic banking crises.

There are several advantages in using SYMBOL. First of all, it yields estimates that are fully compliant with Basel regulation (through the inversion of the FIRB formula) and it explicitly considers correlation in banks' assets and contagion via the interbank market. However, as clearly stated in Public Finance in EMU (2011), the following points should be noted:

i) The main assumption currently behind SYMBOL is that banks' assets consist entirely of loans, so that all capital requirements are considered as for credit risk. Except for very large banks with extensive and complex trading activities, this assumption is not excessively distortive as the credit risk component of capital requirements usually accounts for a very large share of total capital requirements.

ii) Splitting assets/loans into classes for which different obligors' specific probabilities of default are computed would be desirable in order to refine the results of the simulations. However, the currently available public information contained in the

Bankscope database does not allow this as information on the split of capital requirements per asset class is missing.

iii) SYMBOL does not include any interconnection between the risk of default associated with banks and that associated with sovereigns.

These points could be addressed in future research. A sensitivity analysis that quantifies how much of the changes in results is due to the introduction of different settings/regulatory frameworks would also be desirable.

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Chapter 3

The role of contagion in financial crises: an uncertainty test on interbank patterns

3.1 Introduction

The recent financial crisis poses the attention on the interconnection between financial institutions: the idea of "too interconnected to fail" clearly explains that some financial institutions are crucial nodes in the global financial system and therefore they represent a potential source of systemic risk. Systemic risk was defined by G10 in 2001 as '… the risk that an event will trigger a loss of economic value or confidence in, and attendant increases in uncertainty about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy.'[1] The severity of the impact of systemic risk on the overall economy depends on the level of interconnection between financial institutions (or, more generally, market participants).

As explained by De Bandt et al. (2009), systemic risk can materialize in three main forms: contagion, imbalances that have built up over time, and aggregate (macroeconomic) shock causing the simultaneous collapse of a certain number of financial institutions.

In turn, contagion results from two risks: first, the trigger event, that is the risk that at least one component of the system could default (probability of a bank defaulting) and, second, the risk that this shock could propagate through the system (potential impact of the default). As the former can stem from a variety of unexpected situations, and is driven mainly by assets' riskiness and solvency, this research focuses on the latter. Shocks' propagation can be driven by different channels, as Upper (2011) summarizes in the reported Table 3.1.

Table 3.1: *Possible channel of contagion in the banking system*

Asset side	Liability side
Direct effects	

[1] Group of Ten (2001).

Interbank lending	Bank runs
Payment system	Multiple equilibria/fear of other withdrawals
Security settlement	Common pool of liquidity
FX settlement	Information about asset quality
Derivative exposures	Portfolio rebalancing
Equity cross-holdings	Fear of direct effect
Indirect effects	Strategic behaviour by potential lenders
Asset prices	

In these pages I'm going to focus on the interbank channel, that plays a crucial role in the propagation of shocks hitting a banking system. As explained in Rochet and Tirole (1996), if interbank loans are neither collateralized nor insured against, a single bank's failure (or a few banks' failures) may cause a domino effect generating multiple failures.

Literature focused on interbank contagion can be divided in three strands: the first one is represented by theoretical models where contagion is specifically linked to the main characteristics of the considered interbank markets (Allen and Gale, 2000 and Freixas et al., 2000). The second and the third strands are based on empirical simulation. On one hand the authors are focused on network analysis[2]: representing flows in the interbank system by a network structure, they aim to devise the central nodes (i.e. institutions) in order to explore the effect of an adverse event on the entire system.

On the other hand literature empirically examines interbank markets looking at available data on actual interbank exposures. One common problem in dealing with interbank market structures is

[2] See ECB (2010).

that only partial data are available, as balance sheets report only aggregated interbank assets and liabilities. For this reason, it is necessary to integrate through some hypotheses the structure of the interbank flows. The goal of this chapter is to assess how hypothesis of maximum entropy of the interbank matrix (i.e. the matrix of credit and debts among banks) affects the magnitude of a systemic banking crisis in terms of losses suffered by the system.

The estimation of banks' losses requires to have a tool able to generate market scenarios with banks' defaults. This is an issue extensively analyzed by the literature that aims at quantifying the loss distribution associated to Deposit Guarantee Schemes (DGS) and to estimate the optimal size of DGS funds. As I'm going to explain in the next section, the existing literature on this topic is mainly based on structural models for credit risk except for the model proposed by De Lisa et al. (2010)[3], that is able to estimate losses in a banking system by explicitly considering the link between DGS and capital requirements introduced by Basel II. The model is working in two phases: it firstly models the probability of default of a bank and then it estimates the DGS loss distribution by aggregating individual bank losses calculated with Monte Carlo simulations based on the Basel FIRB (Foundation Internal Ratings Based) formula. The model presents features that allow to generate market scenarios with more than one initial default. This is in contrast to what happens in the existing literature about interbank contagion, that starts from the artificial failure on one existing bank and then evaluates potential subsequent failures of the other banks active in the system (following either the fictitious default algorithm provided by Eisenberg and Noe, 2001 or sequential algorithm developed by Furfine, 2003).

The model by De Lisa et al. (2010) deals with contagion in banking systems by directly taking into account the interbank market as a propagation channel for adverse events. In particular, it assumes that once a bank's default occurs, its interbank losses are proportionally shared among its interbank creditor banks. This means that, in order to deal with partial availability of data about interbank exposures, the interbank matrix is approximated with the maximum entropy

(ME) matrix. Their results, referred to the Italian banking system as of 2007, highlight that the introduction of interbank contagion does not imply a shift in the Italian DGS loss distribution, but it leads to a significant increase of its right tail. Since there is no information (or at least not complete information) about the structure of interbank lending, the maximum entropy hypothesis allows the modellers to remain in a sense "neutral". As explained in Upper (2011), there is evidently an analogy with Bayesian estimation: if we are agnostic about a parameter, we tend to use the uniform distribution.

ME is the most common technique used to estimate bilateral exposures from sparse balance sheet data. The cost of such approximation on contagion effects have been explored by Van Lelyveld and Liedorp (2006), Degryse and Nguyen (2007) and Mistrulli (2010). They all find phenomena of either underestimation or overestimation of contagion by comparing results with real existing exposures they have access to. Such a comparison is possible only if details about bilateral exposures are available. Since this is not my specific case, I choose to assess the influence of the maximum entropy hypothesis by verifying if variations in the matrix structure lead to significantly different results in the DGS loss distribution function computed using the model developed by De Lisa et al. (2010). Being conscious of implications of hypotheses on the interbank lending market in a model that estimates systemic losses is crucial for having reliable results and for using such outcomes for regulatory purposes. The methodology in De Lisa et al. (2010) is currently used by the European Commission to evaluate the impact of new regulatory tools in banks' prudential regulations[4]. Thus it is clear that an estimate of banking systems' loss distribution function that is not biased by hypotheses on interbank contagion is necessary for regulatory purposes.

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[3] The model developed in De Lisa et al. (2010) is called SYMBOL (**SY**stemic **M**odel of **B**anking **O**riginated **L**osses).

[4] The model developed by De Lisa et al. (2010) is currently used to address the following issues:

- Reinforcement of DGS
- Introduction of banks' Resolution Funds
- Introduction of an European Tax on financial activities
- Capital Requirement Directive IV
- Annual report Public Finance in EMU

I analyzed results for four countries: Belgium, Ireland, Italy and Portugal. Differences across their banking systems allow to identify if country-specific characteristics are associated with peculiar results.

Interbank exposures are initially modelled using a matrix that maximises the dispersion of banks' bilateral exposures. Contagion results obtained from this scenario are then compared with those achieved with a more concentrated interbank matrix, in order to evaluate if contagion is influenced by hypotheses on interbank exposures. Concentration refers to a situation in which, per each considered bank, exposures are not maximally dispersed, but localized in few banks. Different levels of concentration are tested and obtained losses are compared to the ones resulting from the ME situation.

Results show that relaxing the hypothesis of a maximum entropy interbank matrix affect systemic excess losses in Belgium, Ireland and Portugal, whereas in Italy results are more stable. By contrast, probability distributions are rather robust to variations in the interbank matrix in the four countries.

Furthermore, a distinction is drawn between financial crises in which contagion plays a prominent role and cases in which contagion is not so relevant. When contagion effects are small, systemic excess losses seem to be underestimated by the maximum entropy hypothesis in countries with large interbank exposures. Conversely, with large contagion effects, excess losses are overestimated.

These pages are structured as follows: in the next Section I provide an overview of the literature. Theoretical and empirical papers on contagion in the interbank market are presented together with a picture of models used to generate DGS loss distribution function. Section 3.3 explains the maximum entropy matrix approximation, the algorithm to adjust the matrix of interbank exposures and the model developed by De Lisa et al. (2010) used to generate scenarios. Section 3.4 presents data used to perform the numerical analysis; Section 3.5 shows results obtained testing the effects of changes in the interbank matrix on contagion and loss distribution. Conclusions and directions for future research are explored in Section 3.6.

3.2 Literature review

It is well-known that if a failing bank does not repay its obligations in the interbank market, this could compromise the solvency of its creditor banks and lead to a domino effect in the banking system. Hence, contagion occurs when the financial distress of a single bank affects one bank's ability to pay debts to other financial institutions. Therefore, interlinkages between banks could eventually have an impact on the whole financial system and, beyond that, on the state of the entire economy.

Systemic risk and contagion in the financial system have been extensively analyzed in recent literature. In particular, the idea of interconnection between banks and the role of systemically important financial institutions has a key position in the regulatory debate. The consequences of both the collapse of Long Term Capital Management in 1998 and the failure of Lehman Brothers in 2008 gave inputs to the regulatory discussion about the identification of systemically important financial institutions and the subsequent application of capital charges to them in order to reduce moral hazard linked to the incentive of becoming 'too interconnected to fail'[5].

As reported in Table 3.1 (Upper, 2011), channels of contagion existing in the banking system can be divided in two groups: the ones associated to the liability side of banks' balance sheet and the ones associated to the asset side. Coherently with De Bandt et al. (2009), we can say that the first channel is linked with lack of information that generates contagious withdrawals, and the second one is linked to real exposures. Here I'm interested in the second channel, and specifically in the interbank lending.

[5] See for example Chan-Lau (2009).

Existing literature on financial contagion driven by interbank lending counts both theoretical and empirical papers.

Theoretical studies examine how the structure of the interbank market can influence contagion in the banking system.

Rochet and Tirole (1996) show how interbank exposures can provide incentives of peer monitoring. They set up a theoretical model that examines the trade-off between the positive effect of peer monitoring generated by the existence of interbank lending and the negative effect that the same interbank lending produces by increasing systemic risk. They provide theoretical justification of the fact that more interbank exposures would induce lower bank risk.

Other theoretical studies show that interbank exposures are a channel of crises transmissions since crisis' propagation across the financial system depends on the specific characteristics of the interbank matrix. These studies often apply network theory to the banking system and, in particular, focus on the completeness and connectedness of the interbank matrix. According to Allen and Gale (2000), three main forms of interbank network can be distinguished: (i) the 'complete interbank structure' where banks are linked to all other banks, (ii) the 'incomplete interbank structure' where banks are just linked to neighbouring banks (i.e. banks specialise in particular areas of business or have closer connections with banks that operate in the same geographical or political unit) and (iii) the 'disconnected (incomplete) market structure' where there are different disconnected regions of banks (i.e. banks A and B trade with each other, but not with banks C and D that, in turn, hold deposits in each other). Allen and Gale (2000) argue that contagion effects are less likely to occur in a complete interbank structure, since the relationships with a large number of banks act as a buffer on the impact of a single bank in financial distress. A fourth form of interbank linkage is known as the 'money centre' (Freixas, Parigi and Rochet, 2000) where banks are not linked together but only a central money institution is connected to each financial institution. In this case, it is possible that the failure of a single bank will not trigger the failure of the money centre, but if the money centre itself goes bankrupt this can have a domino effect on the whole interbank market. In addition, a ‘multiple money centre’ structure occurs when the interbank market consists of a number of banking groups, each led by a money centre, where interbank claims are traded solely between banks in the same group.

Beside theoretical papers there are empirical contributions focused on the role played by the interbank market in spreading financial contagion. Empirical contributions are divided in two strands: some papers use data on actual bilateral exposures to test for the possibility of contagion and some others are based on network theory to detect patterns that make networks prone to contagion. These pages are strictly connected with the first strand, but network analysis too is providing significant results about interbank contagion. For example, Nier et al. (2007) analyze how systemic risk depends on four characteristics of the banking systems (net worth, size of the interbank market, degree of connectivity and concentration of the system). Results about degree of connectivity are particularly interesting: the authors find that an increase in interbank connections have two opposite effects: it may act either as a channel to propagate shocks or, on the contrary, as a shock absorber. This mechanism generates an M-shaped relationship between degree of connectivity and banking system resilience (measured in terms of number of defaults). If deeper analyzed, this relationship shows different characteristics according to the level of capitalization of the considered banks: under-capitalized banking systems seem more fragile since interbank linkages act as shock transmitter rather than shock absorber. This is demonstrated by the fact that as connectivity increases, the number of failures keep increasing.

Sachs (2010) employs network analysis to assess the impact of a certain interbank structure on the stability of a variety of stylized financial systems. The author focuses on the structure of the interbank market: she randomly generates interbank matrices with different network structures and then she investigates banks’ failures subsequent to a trigger event represented by a single artificial bank failure. Results show that for financial stability, not only completeness and interconnectedness matter, but also the distribution of interbank exposures within the financial system (measured by entropy).

Empirical contributions using data from bilateral exposures focus on the analysis of a specific country and on the assessment of the danger of domino effects within that specific banking system (Wells, 2004; Upper and Worms, 2004; Elsinger, 2006a, b; Furfine, 2006; Mistrulli, 2010; Van Lelyveld and Liedorp, 2006; Degryse and Nguyen, 2007). The authors have to deal with two main methodological choices:

- How to simulate defaults in the banking system;
- How to estimate the interbank matrix overcoming the lack of data problem.

Regarding the first point, there are two methodologies currently used to model defaults: the fictitious default algorithm provided by Eisenberg and Noe (2001) and the sequential default algorithm provided Furfine (2003). Both methods start from the artificial failure of a bank *j* and then count losses of sequential failures. The main difference among them is that the first method takes into account the simultaneity problem (defaults occurring after the trigger may increase losses at the banks that have failed previously), whereas the second one does not. Despite of this, the majority of papers choose the sequential algorithm.

This contribution uses the model developed by De Lisa et al. (2010) based on Monte Carlo (MC) simulations. In existing literature, Monte Carlo simulations are provided only in two contributions (Elsinger et al., 2006a, b). The first paper analyzes the ten major UK banks in order to outline a framework for systemic financial stability that can capture correlated exposures and credit interlinkages. Starting from an initial state of the banking system described by balance sheet and market data and assuming a stochastic process for bank assets, they simulate via MC the net income of each bank and interbank exposures, characterizing in this way the entire banking system. If, for a given net income and net interbank position, the total value of a bank becomes negative, the bank is insolvent. The authors perform 100 000 scenarios, and the majority of them (more or less the 95% of cases) is characterized by no defaults.

The second paper uses a network model of interbank loans to assess systemic financial stability in the Austrian banking system. They use the Eisenberg and Noe algorithm (2001) modified in order to take into account uncertainty. They assume that each bank has a portfolio holdings composed by interbank credits, loans, bonds and stocks on the asset side and interbank debts and liabilities to nonbanks on the liability side. These positions are exposed to market and credit risk, so they generate scenarios[6] and compute losses on banks' portfolio holdings. Interbank connections are endogenously explained by the network model.

The approach developed by De Lisa et al. (2010) extends the existing literature on deposit insurance by proposing a different estimation of the loss distribution of a DGS based on the Basel II regulatory framework. The existing literature about estimation of the optimal size of the DGS funds proposes two alternative methodologies: one based on option pricing theory (see for example Kuritzkes et al., 2005 for US and Sironi and Zazzara, 2004 for Italy) and the other one adopting a reduced-form model drawn from the pricing of fixed-income securities under default risk (see Duffie et al., 2003). Both approaches are based on structural models for credit risk, which generally require market data in order to empirically apply the proposed methodology. Except for De Lisa et al. (2010), no one else is thus considering the link between banks' capital requirements and the shape and size of DGS loss distribution. The authors firstly estimate the DGS loss distribution taking into account Basel II capital requirements. Second, they take into account the impact of systemic risk that they assume as being generated by two sources: correlation of banks' assets and interbank contagion.

Concerning the modelling of interbank exposures, the lack of data implies that the interbank matrix is not univocally determined. Existing literature dealing with interbank lending tries to overcome this problem in two ways: either using (partial) bilateral data whenever they are available or making some assumptions on the interbank patterns. Some authors have access to detailed data and therefore they are able to construct the real interbank matrix. This doesn't represent the majority of cases, therefore some hypotheses on interbank lending are requested.

[6] For market risk the authors use joint distribution of risk factors (FX, interest rate, stock market changes). For credit risk, they employ an extension of CreditRisk+ Model.

Entropy maximization and cross-entropy minimization (i.e. using additional information) are the most common ways to overcome the lack of data. Some papers try to identify if the estimation of contagion effects (conducted using one of the two methods described above) is biased by maximum entropy hypothesis. My contribution wants to assess the influence of the maximum entropy approximation. In order to do this, results obtained using an interbank matrix maximally disperses (maximum entropy) are compared with results derived from interbank matrices with different levels of concentration obtained by randomly adding zeros inside the matrix itself. Despite of the fact that it may seem unrealistic, this procedure is reasonable in situation where the exact amount of bilateral exposures is unknown and it's necessary to move away from a maximally disperse situation. Cross-entropy minimization has been used in some papers in order to partially overcome the ME assumption, but it can be considered misleading. It consists in adding in the interbank matrix constraints that are generally relative to large exposures as defined in the EU regulatory framework. We know that EU banks are not allowed to have individual counterparty exposures larger than 25% of their capital base. However, short-term exposures of less than one year between financial institutions are exempted from this rule. Since no additional information regarding the maturity of interbank exposures is available, I choose not to add any constraint in the construction of interbank matrices with higher concentration levels.

Looking at existing literature, Wells (2004) uses a sample of UK resident banks to examine contagion driven by direct credit exposures in the UK banking system. The author uses data for the total borrowing and lending positions and he introduces three different estimates to complete the interbank matrix. In the first model he uses maximum entropy to obtain maximally dispersed interbank lending and borrowing, in the second one he incorporates bilateral exposures exceeding a certain threshold for a sample of banks (what is defined as cross-entropy minimization using large exposures data). In the third model further restriction are considered: large banks are assumed to serve as a money centre for smaller banks and foreign banks. Contagion is supposed to occur if a bank suffer a loss that exceeds its Tier 1 capital holdings. Using the sequential algorithm the author records the number of defaults and total assets affected by defaults in each simulation. He finds that different assumptions on the interbank matrix can lead to different levels of contagion. In particular, moving from maximum entropy to a matrix with more details about large exposures implies higher contagion (in terms of number of defaults) but lower asset losses. On the contrary, asset losses are higher in the third model.

Upper and Worms (2004) estimate the danger of contagion in the German banking system driven by credit exposures in the interbank market. They construct bilateral exposures of German banks by using detailed balance sheets provided by the Bundesbank. They estimate interbank matrices using maximum entropy dividing banks in groups (savings banks, cooperative banks, commercial banks and other banks) and by considering different maturity segments for interbank lending. The authors find that the German interbank lending is characterized by a two-tier structure: saving banks and cooperative banks compose the first tier and commercial banks plus head institutions of the two giro systems compose the second one. They use the sequential algorithm and they evaluate the effects of contagion by measuring the number of banks that fail (loss bigger than bank's capital) because of their exposures to the bank that has been artificially brought to failure. They find that contagion in the German market is a serious possibility. They show that losses in the system increase sharply if the loss rate is higher than 40%. Moreover, the introduction of the safety net[7] implies a contagion that remains possible but is much more limited in the scope.

With regard to the Italian interbank market, Mistrulli (2005, 2010) carried out a survey to evaluate contagion in the banking system comparing the hypothesis of the 'complete' structure (obtained maximising the entropy of interbank linkages) with the 'multiple money centre' structure observed in Italy. To this end, a single dataset including actual bilateral exposures is used. Results indicate that the maximum entropy approximation tends to provide a biased estimate of the extent of financial contagion. In particular, the estimated matrix overrates the

[7] Safety net is introduced using the following mechanism:
- Saving banks never fail;
- Public banks guaranteed by the federal government never fail;
- Limited possibility of failure for cooperative banks.

vulnerability to contagion, but this does not hold true in general: it depends on the size of interbank linkages, on recovery rates of interbank exposures and on banks' capitalisation.

Similarly, Degryse and Nguyen (2007) investigated how the structure of the interbank market influences contagion risk, making use of panel data on large exposures to banks in Belgium. In this way, they identified, over time, the pattern of contagion risk due to interbank defaults. They performed a sort of stress test to evaluate how the failure of an individual bank, caused by a sudden and idiosyncratic shock, could cause a systemic crisis in the Belgian financial system. They found that moving from a complete structure to a multiple-money-centre structure (i.e. a situation dominated by higher concentration on the banking market) decreases both the risk and the impact of domestic contagion.

Van Lelyveld and Liedorp (2006) investigate interlinkages and contagion in the Dutch interbank market. As in Wells (2004), they have actual data on large bilateral exposures and they use maximum entropy techniques to estimate only the rest of the interbank matrix. Moreover, Van Lelyveld and Liedorp (2006) made a valuable contribution by comparing the results based on the maximum entropy proxy with survey data on exposures in the Netherlands. In particular, they perform cross-entropy minimization based on data on actual large exposures provided on a confidential basis by the De Nederlandsche Bank. They showed that maximum entropy is not an appropriate approximation for estimating bilateral exposures in a concentrated market (such as the Dutch one).

This chapter aims at assessing how an approximation of interbank linkages that can be very different from the actual linkages affects the evaluation of systemic risk in a financial environment. It simulates the behaviour of the banking system in the presence of contagion, under the maximum entropy assumption (following the method devised by Blien and Graef, 1991). Unlike Lelyveld and Liedorp (2006) and Mistrulli (2010), this chapter does not compare contagion results obtained from the maximum entropy assumption with those derived from an interbank matrix constructed using survey data on bilateral exposures. Moreover, the analysis of existing empirical papers suggests that simulations are triggered by a single artificial failure that causes subsequent collapses in the banking environment considered. The starting point for this chapter is quite different, since simulations with the model developed in De Lisa et al. (2010) make it possible to obtain scenarios with multiple defaults. Banks' assets are considered to be correlated, therefore, in bad economic cycles, multiple banks are exposed to potential failure. In particular, this chapter estimates the distribution of aggregate excess losses (i.e. the losses of a bank that exceed the capital buffer) in the banking system, assuming that the default of one bank can trigger the default of others, which are linked to the failed bank via the interbank matrix.

In order to test the soundness of the maximum entropy assumption, this hypothesis is relaxed to see if variations in the structure of the interbank market lead to significantly different systemic excess losses. Changes in the interbank matrix aim at relaxing the hypothesis of complete markets (as defined in Allen and Gale, 2000): for each analysed bank, a certain proportion of exposures are set to zero and the related contagion effects are compared with those obtained in maximum entropy conditions.

3.3 Methodology

3.3.1 Interbank matrix structure

This analysis assesses the uncertainty in simulations' results that is due to approximations of the interbank matrix. Available data for each bank cover only total credits and debts to other banks, whereas information on bilateral exposures between banks is not publicly available. For this reason, the interbank matrix must be inferred by making assumptions on how interbank debts and credits are spread over the system.

Following Upper and Worms (2004) and Elsinger et al. (2006a, b), the first step is to approximate the interbank matrix with the maximum entropy one, i.e. assuming that banks maximise the dispersion of their interbank credits and debts. This maximum entropy matrix is taken as the reference base in the numerical experiment presented in the next section. Following Upper (2011), the concept of maximizing the entropy is close to the use of the uniform distribution in Bayesian estimation when we are agnostic about a parameter and we don't want to impose any structure to the interbank matrix.

Considering a banking system made up of J banks, interbank exposures can be represented as a $J \times J$ matrix IB = $\{x_{jk}\}$, $j,k = 1,\ldots, J$.

$$IB_{J\times J} = \begin{pmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1J} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2J} \\ x_{31} & x_{32} & x_{33} & \cdots & x_{3J} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{J1} & x_{J2} & x_{J3} & \cdots & x_{JJ} \end{pmatrix}$$

where x_{jk} represents the exposure (debt) of bank j to bank k. Let interbank assets (a) and liabilities (l) be realizations of two marginal distribution $f(a)$ and $f(l)$: x_{jk} can be thought as the realization of their joint distribution. If $f(a)$ and $f(l)$ are independent, $x_{jk}=a_j l_k$. In this way diagonal elements $\{x_{jj}\}$, $j = 1,\ldots,J$ – representing self-exposures – are different from zero, meaning that the bank j is lending to itself. We need thus to modify the problem by setting $x_{jk}=0$ whenever $j = k$ in order to have a matrix like:

$$IB_{J\times J} = \begin{pmatrix} 0 & x_{12} & x_{13} & \cdots & x_{1J} \\ x_{21} & 0 & x_{23} & \cdots & x_{2J} \\ x_{31} & x_{32} & 0 & \cdots & x_{3J} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{J1} & x_{J2} & x_{J3} & \cdots & 0 \end{pmatrix}$$

Only the total amount of interbank credits and interbank debts are known, i.e. $x_k = \sum_j x_{kj}$ and $x_j = \sum_k x_{kj}$ respectively. Moreover, as the samples considered do not cover the whole system, typically the values for total credits and total debits differ, i.e. $\sum_k x_k \neq \sum_j x_j$.

To take this into account, a row and a column must be added to the matrix, representing the net positions with regard to the 'rest of the world'. The interbank matrix is extended to a (*J+1*)×(*J+1*) matrix such that $\sum_k x_k = \sum_j x_j$. Differences are spread over banks in proportion to their total exposure, as follows:

If $\sum_k x_k > \sum_j x_j$ the last column will contain: $\left\{ x_{j\,J+1} = \frac{x_j}{\sum_j x_j}\left(\sum_j x_j - \sum_k x_k\right) \right\}$, $j = 1,\ldots, J$

$$IB_{N+1\times N+1} = \begin{pmatrix} 0 & x_{12} & x_{13} & \cdots & x_{1J} & \frac{x_1}{\sum_j x_j}\left(\sum_j x_j - \sum_k x_k\right) \\ x_{21} & 0 & x_{23} & \cdots & x_{2J} & \frac{x_2}{\sum_j x_j}\left(\sum_j x_j - \sum_k x_k\right) \\ x_{31} & x_{32} & 0 & \cdots & x_{3J} & \frac{x_3}{\sum_j x_j}\left(\sum_j x_j - \sum_k x_k\right) \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ x_{J1} & x_{J2} & x_{J3} & \cdots & 0 & \frac{x_N}{\sum_j x_j}\left(\sum_j x_j - \sum_k x_k\right) \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Symmetrically, if $\sum_k x_k < \sum_j x_j$ the last row will contain:

$$\left\{ x_{J+1k} = \frac{x_k}{\sum_k x_k}\left(\sum_k x_k - \sum_j x_j\right)\right\},\ k = 1,\ldots, J.$$

Keeping these constraints and assuming that the individual interbank exposures in the sample display maximum dispersion, so that each bank lends to each of the others in proportion to its share of the total interbank credit, all the other values can be easily calculated. In this way the largest lender will be the largest creditor for all the other banks, and banks with no debts will evidently result in a column of zeros.

The corresponding matrix is obtained numerically via the RAS algorithm (see Blien and Graef, 1991).

In order to test the robustness of the maximum entropy assumption, variations were introduced in the interbank matrix to evaluate if these changes induce a significant variation in results.

Variations in the matrix of bilateral interbank exposures were introduced with a procedure that preserves the totals but introduces zeros in the IB matrix. In this way an incomplete matrix is obtained that concentrates interbank activities into a limited pre-set number of non-zero values.

The procedure develops as follows:

Considering, for example, a 5×5 IB matrix:

$$IB_{5\times5} = \begin{pmatrix} 0 & x_{12} & x_{13} & x_{14} & x_{15} \\ x_{21} & 0 & x_{23} & x_{24} & x_{25} \\ x_{31} & x_{32} & 0 & x_{34} & x_{35} \\ x_{41} & x_{42} & x_{43} & 0 & x_{45} \\ x_{51} & x_{52} & x_{53} & x_{54} & 0 \end{pmatrix}$$

1) Select, randomly, two different rows and two different columns, which identify four different elements of the matrix (e.g. rows 1 and 2 and columns 3 and 4 identify x_{13}, x_{14}, x_{23} and x_{24}). Provided that all four values are different from zero, these elements are going to be changed in order to obtain a new matrix with one additional zero.

$$IB_{5\times5} = \begin{pmatrix} 0 & x_{12} & 5 & 8 & x_{15} \\ x_{21} & 0 & 6 & 12 & x_{25} \\ x_{31} & x_{32} & 0 & x_{34} & x_{35} \\ x_{41} & x_{42} & x_{43} & 0 & x_{45} \\ x_{51} & x_{52} & x_{53} & x_{54} & 0 \end{pmatrix}$$

2) Evaluate which of the four elements has the lowest value (in this example this is $x_{13} = 5$).
3) The lowest value is subtracted from itself and also from the element in the other row and in the other column $x'_{13} = x_{13} - 5 = 0$; $x'_{24} = x_{24} - 5$ and added to the element in the same row but different column and in the same column but different row $x'_{23} = x_{23} + 5$; $x'_{14} = x_{14} + 5$.

   The new matrix IB*'* will be:

$$IB'_{5\times 5} = \begin{pmatrix} 0 & x_{12} & 5-5 & 8+5 & x_{15} \\ x_{21} & 0 & 6+5 & 12-5 & x_{25} \\ x_{31} & x_{32} & 0 & x_{34} & x_{35} \\ x_{41} & x_{42} & x_{43} & 0 & x_{45} \\ x_{51} & x_{52} & x_{53} & x_{54} & 0 \end{pmatrix} => IB'_{5\times 5} = \begin{pmatrix} 0 & x_{12} & 0 & 13 & x_{15} \\ x_{21} & 0 & 11 & 7 & x_{25} \\ x_{31} & x_{32} & 0 & x_{34} & x_{35} \\ x_{41} & x_{42} & x_{3} & 0 & x_{45} \\ x_{51} & x_{52} & x_{53} & x_{54} & 0 \end{pmatrix}$$

In this way the sums of row and columns are left unchanged, but a zero is introduced where the lowest value was originally placed.

This procedure is then iterated, up to the pre-set number of zeros.

For each country, the process starts with the maximum entropy matrix and adjusts it as described in the previous paragraph in order to produce 20 series of interbank matrices with 20 %, 35 %, 50 %, 65 % and 80 % more elements set to zero (other than the diagonal elements or elements already set at zero). To perform a *ceteris paribus* analysis, for each simulation the variation in the interbank matrix is set randomly, whereas the internal losses suffered by each bank (see next section) are always the same. In this way different results for the same country can only be due to variations in the interbank matrix.

3.3.2 Generating scenarios

In order to verify the effectiveness of contagion, it is necessary to generate market scenarios as close as possible to the real market situation. To do this, a Monte Carlo simulation coherent with a Basel II framework and based on balance-sheet data (see De Lisa et al., 2010) is performed. Correlation between (different) banks’ assets is also taken into account. In particular, SYMBOL considers a level of banks’ assets correlation equal to 50% as found by Sironi and Zazzara (2004).

Monte Carlo simulations are run in order to have 10 000 scenarios with at least one primary (i.e. not induced by previous defaults) default. As you can see from Table 3.2, for three out of four countries (Belgium, Ireland, Portugal) we have the 85% of cases with one primary default and less than 1% of cases with more than five defaults. Italy is quite different because of the width of the banks population that make it possible to obtain about 65% of cases with one primary default and 6% of cases with more than five defaults.

Existing papers using MC simulations (see Elsinger et al., 2006a, b) work in a quite different background: the 95% of cases (over 100 000 simulated scenarios) is represented by situations without any default.

Table 3.2: *Number of primary defaults (before contagion)*

Number of primary defaults	BE	IE	IT	PT
1	8663	8931	6696	8855
2	959	806	1493	840
3	252	183	696	197
4	73	51	330	69
5	29	16	185	21
> 5	24	13	600	18
Total	10000	10000	10000	10000

Following De Lisa et. al. (2010), simulations are based on the following four steps[8]:

1) Estimate the average probability of default of the assets of any individual bank using the Basel II FIRB (Foundation Internal Rating Based) formula (capital requirement K for single exposures) written below:

[8] Refer to chapter 2 “How can we measure the impact of banks’ balance sheets on public finance?” for details about the SYMBOL model.

$$K = \left[LGD * N\left[\frac{1}{\sqrt{1-R}} N^{-1}(PD) + \sqrt{\frac{R}{1-R}} N^{-1}(0.999) \right] - PD * LGD \right] * MaturityAdjustments$$

where

- PD is the probability of default;

- LGD is the loss given default;

- In each bank, *R* represents the correlation between the asset value of a borrower and the systemic factor that reflects the general state of the economy[9]. Thus, as explained in the BIS explanatory note (2005), all borrowers are linked to each other by this single risk factor. *R* is defined as

  $$R = 0.12 * \frac{1-\exp(-50 * PD_i)}{1-\exp(-50)} + 0.24 * \left(1 - \frac{1-\exp(-50 * PD_i)}{1-\exp(-50)}\right) - 0.04 * \left(1 - \frac{S_i - 5}{45}\right)$$

  where S_i represents the firm size (measured in terms of annual sales).

- Maturity adjustments are needed because credit portfolios consist of instruments with different maturities. They are defined as

  $$MaturityAdjustments = (1-1.5B)^{-1} * [1 + (M - 2.5)B]1.06$$

  where *M* is time to maturity and *B* is a smoothed regression maturity adjustment defined as $B=[0.11852-0.05478ln(PD)]^2$

The overall capital requirement for bank *j* is computed as the sum of the capital allocation parameter (*K*) of each exposure *l* multiplied by its amount A_l.

$$K_j = \sum_l K(PD_l) A_l$$

SYMBOL estimates the average PD ($\overline{PD}$) of a bank's asset portfolio by inverting the FIRB formula. In this way the average PD of bank *j* is the probability that allows the actual value of capital requirement for that specific bank (K_j) to be equal to its numerically calculated value. LGD, maturity and size are set to their regulatory values (LGD = 0.45; M = 2.5; S = 50): in this way PD is the only unknown variable in the FIRB formula above.

2) Generate via Monte Carlo a sample of loan losses based on

$$L_{ij} = LGD * N\left[\sqrt{\frac{1}{1-R}} N^{-1}\left(\overline{PD}_j\right) + \sqrt{\frac{R}{1-R}} N^{-1}\left(z_{ij}\right)\right] - \overline{PD}_j * LGD$$

where

$i = 1,..., N$ simulations

$N^{-1}(z_{ij}) \sim N(0,1) \forall i, j$

---

[9] Recall that each asset value X_i can be split between a common (systemic) factor C and an idiosyncratic factor ε_i $X_i = \sqrt{R}C + \sqrt{1-R}\varepsilon_i$

$$\mathrm{cov}(z_{ij}, z_{ik}) = 0.5 \ \forall j \neq k$$

MC is performed via random shocks for $N^{-1}(z_{ij})$ (the assumption of normal distribution is needed in order to reproduce the distribution of bank losses that is implied in Basel II).

3) Primary banks' simulated losses are then compared with banks' capital. Whenever losses net of provisions exceed total capital, bank *j* is considered to default in simulation *n*.

   These net losses are recorded (when at least one bank defaults) as 'no contagion losses'.

4) Estimate the distribution of aggregate losses for single countries via the combination of individual banks' excess losses.

This procedure creates a wealth of synthetic market scenarios that are fully compliant with Basel II regulation and that consider correlation between banks' assets: they represent the starting point for testing contagion effects.

Following James (1991), it was assumed that, whenever a bank defaults, 40 % of the amount of its interbank debts are passed onto creditor banks and distributed between them, so that losses with contagion (via the interbank market) L^C can be written as:

$L^c_{ij}(z_{ij}, \overline{PD}_j, IB) = L_{ij}(z_{ij}, \overline{PD}_j) + \sum_k D_k x_{kj}$ where $D_k = 1$ if bank *k* defaults, and zero otherwise.

Considering this, bank *j* defaults when

$$L^c_{ij}(z_{nj}, \overline{PD}_j, IB) \geq K_j .$$

Contagion is looped up to the cycle where no more banks default.

Finally, net losses $L^c_{ij}(z_{ij}, \overline{PD}_j, IB) - K_j$ are recorded.

Simulations were performed in order to have 10 000 significant values for each country and for each interbank matrix. Setting the same starting seed in a random number generator assures that differences in contagion results are only due to interbank matrix variations.

3.4 Data

Some authors point out that different features of banking systems could lead to different effects of the maximum entropy hypothesis. For this reason, the analysis was conducted on four banking systems: Belgium (BE), Italy (IT), Ireland (IE) and Portugal (PT). These banking systems show different banks' concentration ratio and business models. This makes it possible to evaluate if the impact of changes in the hypotheses over the interbank matrix is related to countries' specific characteristics.

Data are based on the *Bankscope* dataset, as of December 2009, integrated with European Central Bank and central banks' values.

Table 3.3 contains aggregate information about input data for each country.

Table 3.3*: Description of the samples used for simulations*

	Number of banks	**Sample % population**	**Capital (m€)**	**Total assets (m€)**	**Interbank debts (m€)**	**Interbank credits (m€)**
BE	23	82.26 %	48 401	878 336	97 493	84 727
IE	24	101.91 %[10]	65 392	1 221 181	276 738	148 729
IT	473	81.81 %	270 876	2 827 051	188 375	195 958
PT	14	66.49 %	26 341	323 762	43 561	34 504

	Capital/total assets	**Interbank debts/total assets**	**Interbank credits/total assets**	**Herfindhal index (over total assets)**	**Herfindhal index (over**	**Herfindhal index (over interbank credits)**

[10] IE data used to constrcut the Sample % Population are derived both from ECB and from IE central bank.

					interbank debts)	
BE	0.055	0.111	0.096	0.293	0.304	0.256
IE	0.054	0.227	0.122	0.154	0.177	0.214
IT	0.096	0.067	0.069	0.054	0.092	0.117
PT	0.081	0.135	0.107	0.259	0.228	0.345

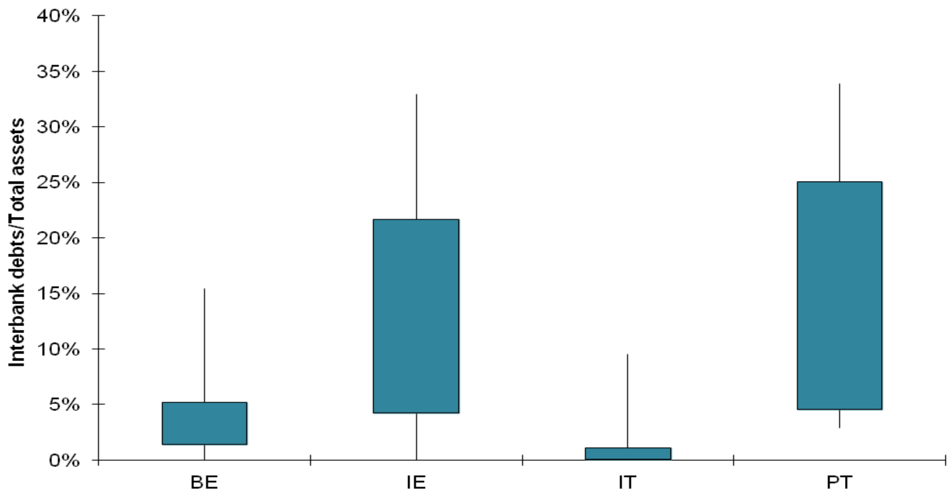
The sample of banks covered in each country ('sample population') is calculated with reference to the amount of total assets reported by the ECB[11].

Capitalisation levels, measured by the capital/total assets ratio, first approximate the extent to which banks are resilient to defaults of their own assets. We have to remind that such resilience also depends on the riskiness of the assets, which is taken into account in the scenario-generating process when we compute the probability of default of the assets of each single bank.

Columns containing interbank volumes represent the size of interbank debts and credits over total assets. Obviously, countries where interbank exposures have significant volumes compared to total assets are more exposed to a shock transmission occurring via the interbank channel. If we look at aggregate data reported above, we can see that Ireland and Portugal have the most intense interbank activity. Going into single banks details (Figure 3.1 and Table 3.4), we can notice that for the two countries interbank exposures account for a large portion of total assets.

Figure 3.1: *Interbank debts and credits as share of total assets*

[11] Source: European Central Bank (2010), EU banking structures: http://www.ecb.int/pub/pdf/other/eubankingstructure201009en.pdf.



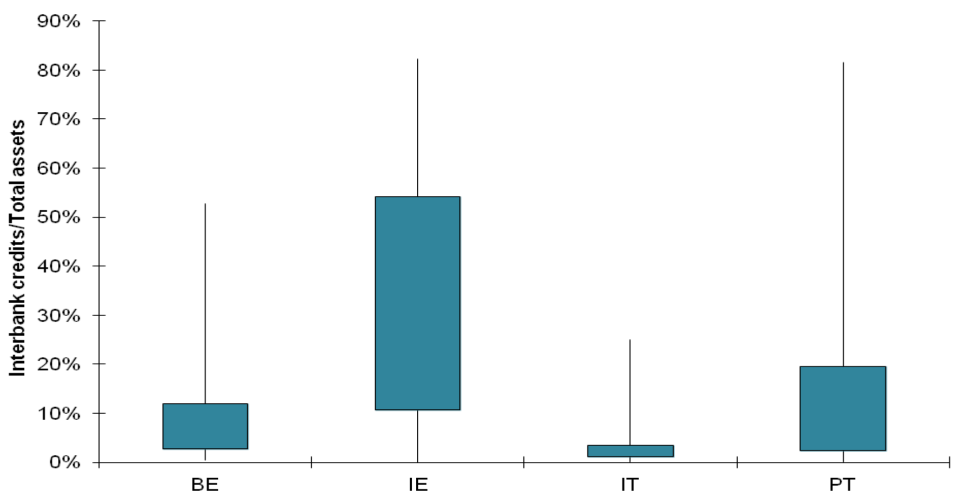


Table 3.4: *Interbank debts and credits as share of total assets*

IB-/TA	BE	IE	IT	PT
Min	0%	0%	0%	3%
1st quartile	1%	4%	0%	5%
Median	3%	13%	0%	9%

IB+/TA	BE	IE	IT	PT
Min	1%	0%	0%	0%
1st quartile	3%	11%	1%	2%
Median	6%	32%	2%	11%

3rd quartile	5%	22%	1%	25%
Max	15%	33%	10%	34%

3rd quartile	12%	54%	3%	19%
Max	53%	82%	25%	82%

If we compare interbank exposures and capital (Tables 3.5), we can see that in many cases IB debts and credits are even larger than banks' capital.

Table 3.5: *Interbank debts and credits as share of capital*

IB-/CAPITAL	**BE**	**IE**	**IT**	**PT**
Min	1%	0%	0%	27%
1st quartile	19%	44%	0%	49%
Median	42%	145%	2%	115%
3rd quartile	81%	376%	9%	217%
Max	167%	842%	403%	728%

IB-/CAPITAL	**BE**	**IE**	**IT**	**PT**
Min	9%	0%	0%	1%
1st quartile	31%	111%	10%	32%
Median	85%	362%	17%	150%
3rd quartile	235%	939%	31%	210%
Max	1281%	2105%	1551%	1751%

Levels of interbank that are even higher than the capital make realistic and concrete the possibility of contagion via the interbank market in the considered banking systems.

In the Table 3.3 Herfindhal indices are computed: they monitor concentration in the banking system relative to total asset and interbank exposures. The index is generally calculated as:

$$H = \sum_{j=1}^{J} s_j^2 ,$$

where s_j is the market share of firm j in the market with respect to the variable considered (total assets, interbank debts and credits).

Looking at the tables above, we can notice that we are considering heterogeneous countries. This is true not only in terms of interbank exposures, but also in terms of capitalization and sample size.

Belgium has a small number of banks and, according to its Herfindhal indices, a highly concentrated banking system in terms of total assets and interbank exposures.

The Irish banking system is not highly concentrated and is made up of a small number of banks highly exposed in the interbank market. I expect that contagion effects will be more intense in Ireland because of the high incidence of the interbank lending activity over total assets and capital.

Italy has the largest number of banks, high capitalisation, low interbank exposures and low Herfindhal indices.

Portugal has the smallest number of banks, a high capitalisation level and, together with Belgium, the highest level of concentration in terms of both total assets and interbank exposures.

3.5 Results

3.5.1 Effects on contagion

The consequences of assuming ‘maximum entropy’ for interbank exposures are not evident *a priori*. On one hand, the maximum entropy assumption could lead to underestimation of contagion risk: the consequences of a default are actually spread across all the other banks, limiting the effects on each single bank. On the other hand, this assumption reflects the connectedness between all banks, even where no real interbank links exist. For this reason there is the concrete possibility of creating contagion among banks. It is thus necessary to verify the influence of variations in the interbank matrix for the whole probability distribution of estimated losses.

As expected, concentration in the interbank matrix does affect variability. In particular, the higher the concentration in interbank connections (number of zeros in the interbank matrix), the higher the variability in results. Moreover, higher interbank values (Ireland) result in higher variability, while a higher number of banks (Italy) possibly induces more stability.

In this regard, Table 3.6 reports the average ratios constructed as standard error over average. Remember that simulations are run in order to have 10 000 scenarios with at least one default in each country. For each scenario 20 different interbank matrices were constructed for each concentration level, so that in the end contagion in each country can be monitored by five matrices (one for each concentration level) with dimensions 10 000 x 20, for both losses and defaults. Variability in a single banking system is thus evaluated with the average value of the standard error/average ratio calculated for each row of the five matrices.

Table 3.6*: Variability — average value in standard error of contagion simulations results*

	+ 20 % zeros	**+ 35 % zeros**	**+ 50 % zeros**	**+ 65 % zeros**	**+ 80 % zeros**
BE	0.6 %	0.7 %	2.1 %	3.3 %	5.7 %
IE	11 %	26 %	34 %	56 %	78 %
IT	0.004 %	0.008 %	0.013 %	0.023 %	0.045 %
PT	2 %	4 %	4 %	6 %	7 %

The general trend is an increase in variability as the simulation moves up from a situation with 20 % of zeros added in the interbank matrices to 80 % of zeros added. This trend is confirmed in all four countries considered, even if differences between them can be seen from the differences in the magnitude of variability. As expected, the largest variability is associated to IE, that is characterized by low capital and high interbank exposures. Conversely, IT – whose banking system has high capitalization, moderate interbank activity and a large analyzed sample – has the smallest variability.

We also investigate if changes in the interbank matrix produce an effect on losses aggregated on the basis of the magnitude of contagion. Tables 3.7 to 3.10 and 3.11 to 3.14 report three possible magnitude levels, individualised by the amount of losses originated in the cases of maximum entropy and of no contagion. In this regard, it must be remembered that simulations were run with and without contagion, in order to evaluate the effects of linkages between banks.

In detail, Tables 3.7 to 3.10 represent the average number of defaults, while Tables 3.11 to 3.14 report the average excess losses calculated per country. The 'overall' column represents results obtained over the 10 000 simulated scenarios, while the other three columns show the number of defaults and losses split on the basis of the magnitude of contagion. More specifically:

- NO CONTAGION contains cases where:
  $ExcessLoss(NoContagion) = ExcessLoss(BaseScenario)$
- SMALL CONTAGION contains cases where:
  $ExcessLoss(BaseScenario) - ExcessLoss(NoContagion) \leq ExcessLoss(NoContagion)$
- LARGE CONTAGION contains cases where:
  $ExcessLoss(BaseScenario) - ExcessLoss(NoContagion) > ExcessLoss(NoContagion)$

The 'BASE' row refers to the maximum entropy situation, whereas +20 %, +35 %, +50 %, +65 % and +80 % indicate subsequent changes in the interbank matrix.

Table 3.7: *Number of defaults by contagion magnitude — Belgium*

BE		**CONTAGION**		
	Overall (10 000 cases)	**NO (6 747 cases)**	**SMALL (2 275 cases)**	**LARGE (978 cases)**
BASE	1.84	1.00	2.67	5.75
+20 %	1.85	1.00	2.68	5.76

+35 %	1.87	1.00	2.72	5.82
+50 %	1.90	1.00	2.80	5.97
+65 %	1.96	1.04	2.95	6.00
+80 %	2.12	1.07	3.37	6.48

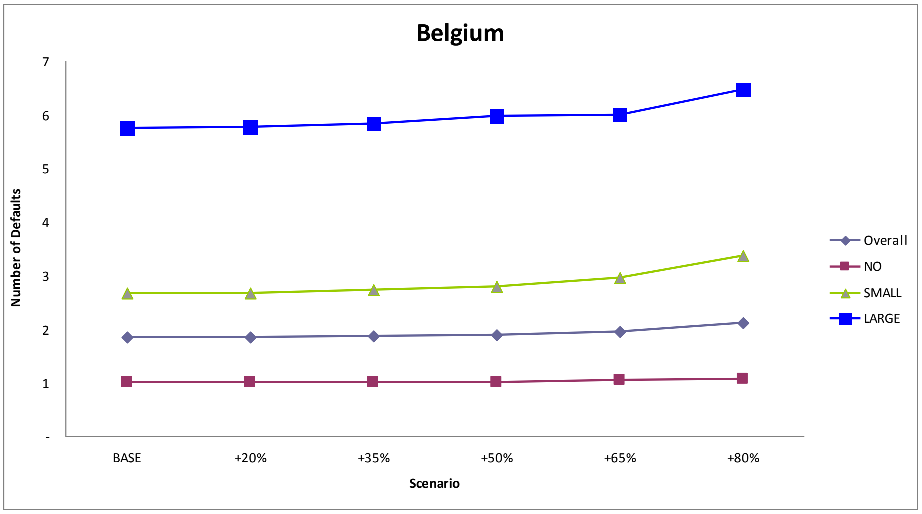


***Table 3.8**: Number of defaults by contagion magnitude — Ireland*

IE		**CONTAGION**		
	Overall (10 000 cases)	**NO (6 174 cases)**	**SMALL (937 cases)**	**LARGE (2 889 cases)**
BASE	4.41	1.00	2.21	12.40
+20 %	4.46	1.03	2.41	12.45
+35 %	4.51	1.11	2.81	12.35
+50 %	4.65	1.19	3.73	12.34
+65 %	4.82	1.49	4.30	12.10
+80 %	5.51	2.34	6.58	11.94

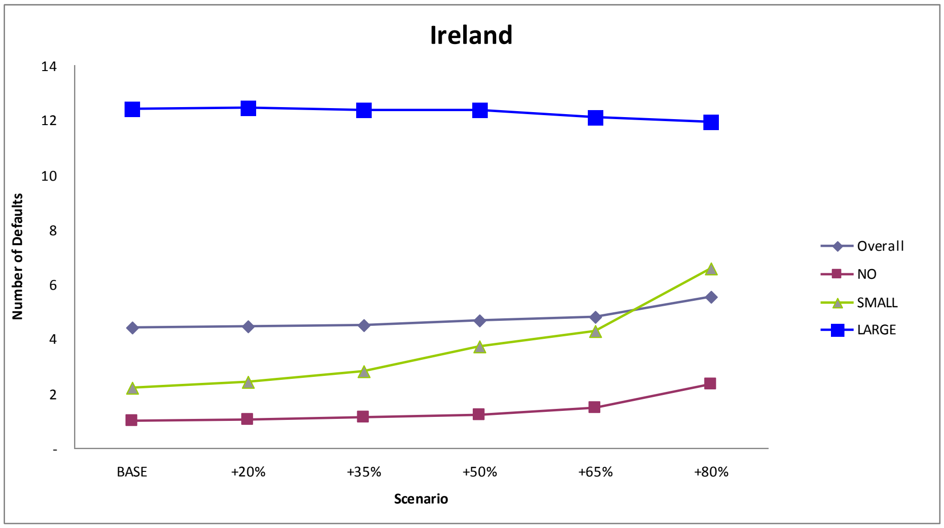


***Table 3.9**: Number of defaults by contagion magnitude — Italy*

IT		**CONTAGION**		
	Overall (10 000 cases)	**NO (6 694 cases)**	**SMALL (3 305 cases)**	**LARGE (0 cases)**
BASE	2.15	1.00	4.48	-
+20 %	2.15	1.00	4.48	-
+35 %	2.15	1.00	4.48	-
+50 %	2.15	1.00	4.48	-
+65 %	2.15	1.00	4.48	-
+80 %	2.15	1.00	4.48	-

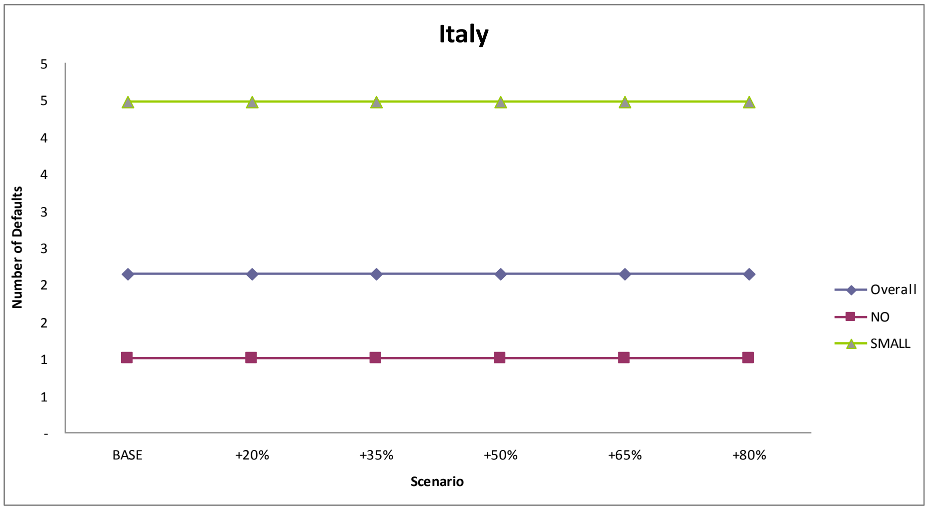
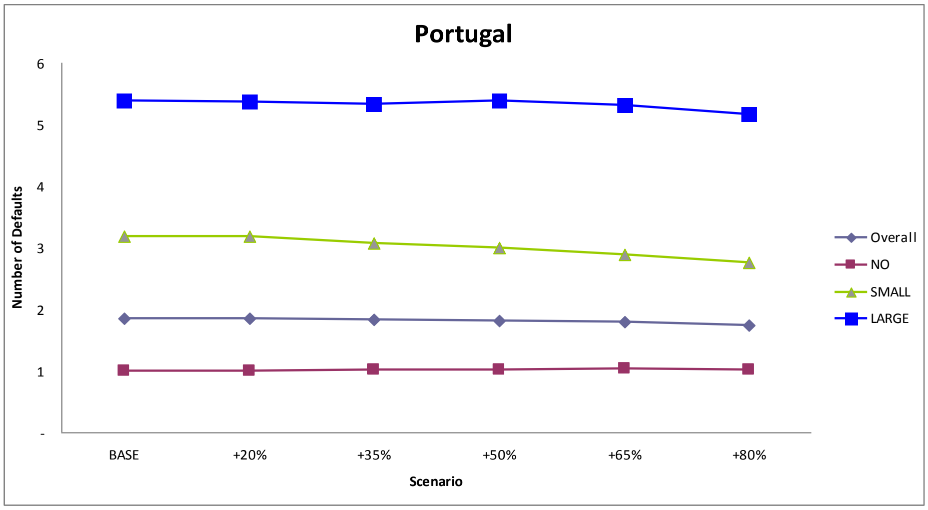


Table 3.10: *Number of defaults by contagion magnitude — Portugal*

PT	**CONTAGION**			
	Overall (10 000 cases)	**NO (6 814 cases)**	**SMALL (2 478 cases)**	**LARGE (708 cases)**
BASE	1.85	1.00	3.19	5.39
+20 %	1.85	1.00	3.18	5.38
+35 %	1.83	1.01	3.07	5.33
+50 %	1.81	1.01	2.99	5.39
+65 %	1.79	1.03	2.88	5.31
+80 %	1.74	1.01	2.76	5.16



Looking at Tables 3.7 to 3.10 we can notice a difference in the way ME is influencing the number of losses in the three levels of contagion magnitude. In particular, in case of NO and SMALL contagion, ME tends to underestimate failures compared to what happens in the case of highest concentration (+80%). In case of LARGE contagion, there are differences among countries. For IE and PT, ME is overestimating the number of defaults. Conversely underestimation persists in BE (IT has no cases that can be classified as LARGE contagion).

Table 3.11: *Average value of losses by contagion magnitude (th €) — Belgium*

BE	**CONTAGION**			
	Overall (10 000 cases)	**NO (6 747 cases)**	**SMALL (2 275 cases)**	**LARGE (978 cases)**
BASE	2 696 176	498 464	5 063 463	12 352 041
+20 %	2 693 324	498 724	5 065 719	12 314 761
+35 %	2 693 778	498 956	5 064 582	12 320 454
+50 %	2 703 282	499 291	5 109 217	12 311 490
+65 %	2 710 214	504 140	5 147 584	12 259 669
+80 %	2 761 571	512 407	5 394 238	12 153 998

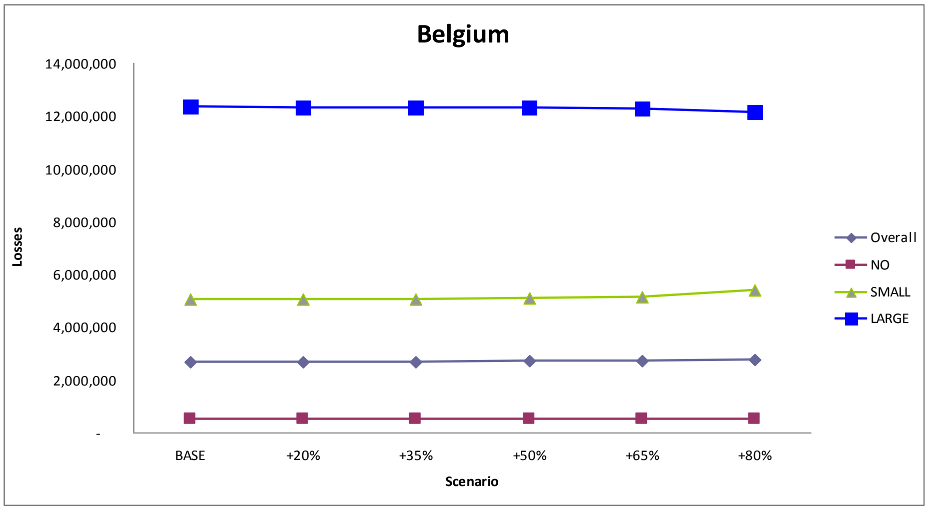


***Table 3.12**: Average value of losses by contagion magnitude (th €) — Ireland*

IE	**CONTAGION**			
	Overall (10 000 cases)	**NO (6 174 cases)**	**SMALL (937 cases)**	**LARGE (2 889 cases)**
BASE	16 998 231	989 367	2 394 299	55 946 867
+20 %	17 049 103	1 074 374	3 407 988	55 612 516
+35 %	16 968 441	1 291 853	5 529 794	54 180 373
+50 %	17 206 620	1 565 217	9 522 706	53 125 572
+65 %	17 321 954	2 517 032	12 076 994	50 662 249
+80 %	19 941 129	6 014 341	22 203 313	48 969 972

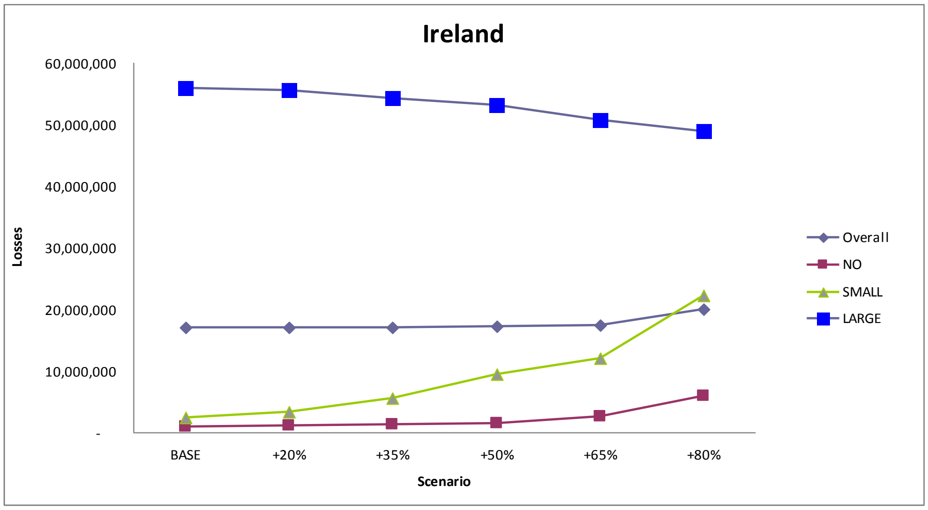


***Table 3.13**: Average value of losses by contagion magnitude (th €) — Italy*

IT	**CONTAGION**			
	Overall (10 000 cases)	**NO (6 694 cases)**	**SMALL (3 305 cases)**	**LARGE (0 cases)**
BASE	171 048	47 199	421 817	-
+20 %	171 046	47 199	421 812	-
+35 %	171 045	47 199	421 807	-
+50 %	171 052	47 199	421 828	-
+65 %	171 047	47 199	421 815	-
+80 %	171 042	47 200	421 800	-

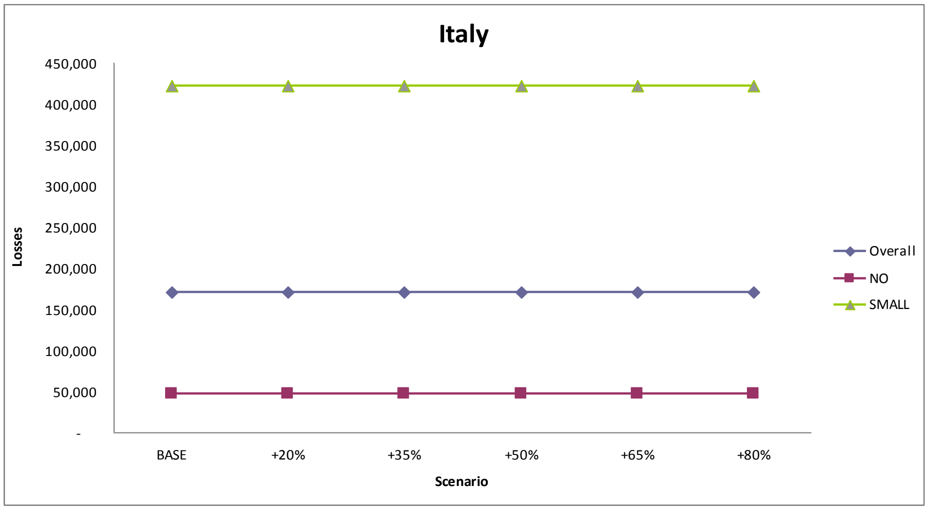
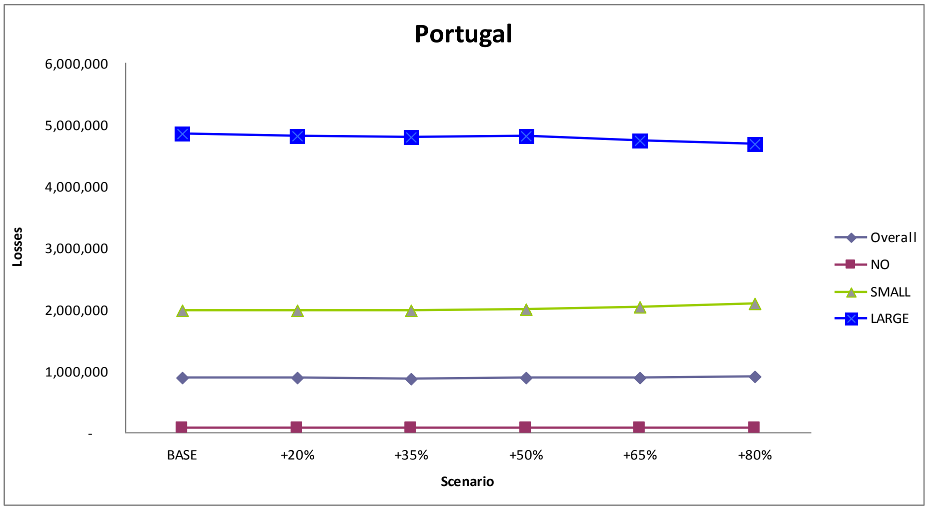


Table 3.14*: Average value of losses by contagion magnitude (th €) — Portugal*

PT		CONTAGION		
	Overall (10 000 cases)	**NO (6 814 cases)**	**SMALL (2 478 cases)**	**LARGE (708 cases)**
BASE	881 506	68 602	1 984 053	4 846 226
+20 %	881 388	68 664	1 990 277	4 822 161
+35 %	879 098	68 842	1 989 835	4 789 649
+50 %	884 939	68 910	2 007 381	4 810 091
+65 %	887 535	69 586	2 037 210	4 735 842
+80 %	898 572	70 164	2 093 690	4 688 501



Looking at Tables 3.11 to 3.14, the average results ('Overall' column) clearly indicate that, considering all 10 000 scenarios, changes in the interbank matrix (zeros added) do not significantly influence the amount of excess losses estimated in the base case of maximum entropy. The only exception is Ireland +80 %, where the amount of losses jumps when the extreme concentration level is reached. Nevertheless, some differences originate when the results are split into groups selected by the size of contagion. In the small contagion case, the maximum entropy hypothesis (base values) tends to lead to underestimation of excess losses, whereas in big crises (large contagion) maximum entropy seems to overestimate contagion effects (as found by Mistrulli, 2010).

Looking at differences between countries, banking systems with a large number of banks (Italy) tend to have more stability in results, producing almost the same estimates for excess losses despite the hypothesis over the interbank matrix.

Countries with a smaller number of banks experience more significant changes in the amount of losses. In particular, contagion is more vulnerable to changes in the interbank structure in countries that have more sizable interbank exposures (and lower capitalisation) and are therefore more exposed to financial contagion (Ireland). In these situations the ‘no contagion’ and ‘small contagion’ simulations are highly underestimated, whereas ‘large contagion’ cases are slightly overestimated.

3.5.2 Effects on losses probability distribution

Different evaluations can be found when considering the probability distribution of losses.

Tables 3.15 to 3.18 (attached at the end of the chapter) report, for each country, the distribution of the 10 000 simulated scenarios. In each table, column 1 (no contagion) shows the magnitude of systemic excess losses without contagion effects, column 2 (base scenario) shows results for the baseline scenario (i.e. under the maximum entropy assumption) and columns 3 to 8 contain results for the matrices an increase of 20 %, 35 %, 50 %, 65 % or 80 % of matrix elements set to zero. Tables 3.19 to 3.22 represent variations (%) of the average value of losses from the ME situation.

Table 3.19: *Average value of losses: differences with the BASE scenario— Belgium*

BE	**Differences with the BASE scenario**				
	+ 20% zeros	**+ 35% zeros**	**+ 50% zeros**	**+ 65% zeros**	**+ 80% zeros**
90%	-0,11%	-0,02%	0,08%	0,58%	3,09%
80%	0,12%	0,32%	1,83%	3,08%	12,43%
70%	0,53%	1,06%	4,60%	6,84%	18,15%
60%	-0,03%	0,06%	-0,23%	1,27%	1,66%
50%	-0,02%	-0,03%	-0,16%	0,22%	0,27%
40%	0,00%	-0,03%	-0,05%	0,28%	0,44%
30%	-0,01%	0,00%	-0,01%	0,09%	0,09%
20%	0,04%	0,04%	0,06%	0,10%	0,11%
10%	0,01%	0,01%	0,01%	0,09%	0,09%

Table 3.20: Average value of losses: differences with the BASE scenario— Ireland

IE	Differences with the BASE scenario				
	+ 20% zeros	+ 35% zeros	+ 50% zeros	+ 65% zeros	+ 80% zeros
90%	0,10%	0,03%	0,49%	0,49%	0,39%
80%	0,07%	-0,70%	-1,49%	-3,77%	3,52%
70%	-0,54%	19,06%	66,45%	85,77%	420,61%
60%	1,65%	5,56%	15,27%	31,82%	249,39%
50%	2,73%	6,02%	14,82%	26,48%	111,85%
40%	1,05%	4,06%	10,29%	20,50%	61,38%
30%	0,70%	2,52%	6,96%	14,07%	28,19%
20%	0,37%	1,44%	4,11%	8,47%	14,84%
10%	0,14%	0,94%	2,72%	5,74%	9,77%

Table 3.21: Average value of losses: differences with the BASE scenario— Italy

IT	Differences with the BASE scenario				
	+ 20% zeros	+ 35% zeros	+ 50% zeros	+ 65% zeros	+ 80% zeros
90%	0,00%	0,00%	-0,01%	-0,03%	-0,04%
80%	0,01%	-0,01%	-0,01%	-0,02%	-0,03%
70%	0,00%	0,01%	0,02%	0,03%	0,03%
60%	0,00%	0,00%	0,00%	0,00%	0,00%
50%	0,00%	0,00%	0,00%	0,00%	0,01%
40%	0,00%	0,00%	0,00%	0,00%	0,00%
30%	0,00%	0,00%	0,00%	0,00%	0,00%
20%	0,00%	0,00%	0,00%	0,00%	0,00%
10%	0,00%	0,00%	0,00%	0,00%	0,00%

Table 3.22: Average value of losses: differences with the BASE scenario— Portugal

PT	Differences with the BASE scenario

	+ 20% zeros	+ 35% zeros	+ 50% zeros	+ 65% zeros	+ 80% zeros
90%	0,16%	0,03%	1,26%	2,19%	5,18%
80%	-0,47%	-1,26%	1,21%	3,25%	11,25%
70%	-0,61%	-1,97%	-1,22%	-2,12%	-2,11%
60%	-0,17%	-0,19%	-0,60%	-0,62%	-1,73%
50%	-0,03%	0,10%	-0,33%	0,07%	-0,77%
40%	0,04%	0,22%	-0,08%	0,27%	-0,37%
30%	-0,17%	-0,32%	-0,66%	-0,41%	-1,10%
20%	-0,04%	0,00%	-0,12%	0,04%	-0,28%
10%	0,01%	0,09%	0,05%	0,23%	0,01%

In Tables 3.15 to 3.18, the comparison between columns 1 and 2 could be useful to address the effects of contagion. For instance, Tables 3.15 and 3.18 indicate that contagion in the Belgian and Portuguese banking systems has no effect on systemic excess losses under the 40th percentile of the distribution. In IE the effects are visible starting from the 10th percentile, confirming that large interbank exposures lead to more severe domino effects. Italy is less exposed, since contagion effects are significant only looking at the 90th percentile.

For each of the five classes of variation (20%, 35% 50%, 65% and 80%), I estimated 20 probability distributions obtained via 20 different interbank matrices. The averages and standard errors are reported in Tables 3.15 to 3.18.

Results show that variations in the structure of the interbank matrix do not really affect the probability distribution of banking crisis estimates in three out of four countries. This is probably (and almost partially) due to the fact that when the interbank matrix is incomplete, contagion affects some banks and does not affect others, thus inducing different results. When considering the whole system, larger effects on some banks and lower on others balance out and the final distribution (which is re-ordered by crisis size) is not deeply affected.

Looking at single countries, Italy does not show differences, and this is probably due to the width of the used sample. In this case, ME assumption is not too restrictive, since it leads to the same results obtained in case of higher concentration in the interbank market.

Belgium and Portugal are similar for sample characteristics and therefore they show similar results. Tables 3.15, 3.18, 3.19 and 3.22 show that ME is not influencing results: the most significant variation is associated to maximum concentration level (+80%) in Belgium starting from the 60^{th} percentile.

Ireland is the only country showing significant differences. In particular, the maximum level of concentration highlights extreme variations with respect to the ME case.

3.6 Conclusions

This chapter tests maximum entropy approximation for the interbank matrix in simulating contagion effects in banking systems. An uncertainty test is performed on the maximum entropy matrix by developing an algorithm that allows more concentrated interbank exposures to be obtained. A Monte Carlo method is applied to generate banking crises scenarios that are used to test contagion effects. Results obtained from the maximum entropy interbank matrix are then compared with the results derived from more concentrated matrices.

The probability distribution of losses is rather stable even with 80 % more zeros in the matrix for three out of four countries.

Conversely, when considering the magnitude of contagion, it can be seen that excess losses tend to be underestimated when the maximum entropy matrix is used in banking systems with large interbank exposures and in ‘small contagion crises’. Otherwise ‘large contagion crises’ tend to be associated with overestimation of excess losses.

As in Mistrulli (2010), it's clear that underestimation of contagion by maximum entropy is heightened by the specific features of the banking system. More specifically, high levels of capitalisation, low interbank exposure and large samples seem to produce more stable results. On the other hand, low capitalisation, high interbank exposure and a small number of banks result in underestimation of excess losses in 'small contagion crises' and overestimation in 'large contagion crises'. A summary of characteristics and results is presented in the Table 3.23.

Table 3.23: *Summary of main results*

	Banking systems' characteristics			Number of defaults			Average value of losses		
	Capital/Total assets	**Interbank debts/Total assets**	**Interbank credits/Total assets**	**N**	**SMALL**	**LARGE**	**N**	**SMALL**	**LARGE**
BE	Low	Low	Low	-	-	-	-	-	+
IE	Low	High	High	-	-	+	-	-	+
IT	High	Low	Low	=	=	na	=	=	na
PT	High	High	High	-	+	+	-	-	+

Therefore, results for different countries seem to be clearly affected by certain characteristics of the banking system. Precise quantification of their individual effects would go beyond the scope of this chapter. Nevertheless it is worth developing this approach in future research and performing a sensitivity analysis in order to better quantify the effects of banking systems' characteristics on financial contagion.

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__Table 3.15:__ Estimated losses probability distribution — Belgium

BE	No contagion	Base scenario	+20 % zeros		+35 % zeros		+50 % zeros		+65 % zeros		+80 % zeros	
			Average	Standard error %	Average	Standard error %	Average	Standard error %	Average	Standard error %	Average	Standard error %
90 %	4 963 902	8 076 588	8 067 476	1%	8 075 254	1%	8 083 277	1%	8 123 097	2%	8 325 802	5 %
80 %	2 124 436	3 165 878	3 169 533	0%	3 176 077	1%	3 223 853	3%	3 263 529	4%	3 559 248	8 %
70 %	696 941	1 260 621	1 267 342	1%	1 274 006	1%	1 318 665	6%	1 346 789	7%	1 489 448	13 %
60 %	238 197	269 098	269 019	0%	269 248	0%	268 486	1%	272 527	2%	273 569	4 %
50 %	113 708	119 845	119 820	0%	119 809	0%	119 648	0%	120 114	1%	120 170	1 %
40 %	60 175	61 529	61 526	0%	61 513	0%	61 499	0%	61 702	1%	61 801	1 %
30 %	31 970	32 241	32 239	0%	32 243	0%	32 237	0%	32 270	0%	32 271	0 %
20 %	16 151	16 249	16 255	0%	16 256	0%	16 259	0%	16 266	0%	16 267	0 %
10 %	6 500	6 517	6 517	0%	6 517	0%	6 518	0%	6 522	0%	6 523	0 %

Table 3.16: *Estimated losses probability distribution — Ireland*

IE	No contagion	Base scenario	+20 % zeros		+35 % zeros		+50 % zeros		+65 % zeros		+80 % zeros	
			Average	Standard error %	Average	Standard error %	Average	Standard error %	Average	Standard error %	Average	Standard error %
90 %	4 985 377	62 698 542	62 758 442	0%	62 717 637	1%	63 004 224	1%	63 004 066	2%	62 939 981	3%
80 %	2 657 548	51 321 600	51 355 471	2%	50 964 341	4%	50 558 473	7%	49 386 188	8%	53 126 401	7%
70 %	1 610 770	6 867 626	6 830 817	2%	8 176 396	91%	11 430 821	103%	12 758 165	87%	35 753 569	37%
60 %	987 499	2 094 352	2 128 881	2%	2 210 744	12%	2 414 177	13%	2 760 687	22%	7 317 439	111%
50 %	591 401	943 087	968 819	4%	999 867	7%	1 082 851	10%	1 192 853	15%	1 997 922	34%
40 %	338 844	470 510	475 435	4%	489 601	8%	518 941	12%	566 961	19%	759 291	40%
30 %	182 764	225 856	227 429	3%	231 543	6%	241 571	8%	257 633	13%	289 531	16%
20 %	87 586	98 216	98 576	2%	99 634	3%	102 256	4%	106 534	7%	112 791	10%
10 %	33 409	35 908	35 957	1%	36 246	2%	36 883	3%	37 968	5%	39 415	9%

Table 3.17: *Estimated losses probability distribution — Italy*

IT	No contagion	Base scenario	+20 % zeros		+35 % zeros		+50 % zeros		+65 % zeros		+80 % zeros	
			Average	Standard error %	Average	Standard error %	Average	Standard error %	Average	Standard error %	Average	Standard error %
90 %	314 591	316 000	315 998	0 %	315 992	0 %	315 954	0 %	315 892	0 %	315 887	0 %
80 %	119 961	120 194	120 204	0 %	120 184	0 %	120 188	0 %	120 174	0 %	120 158	0 %
70 %	65 722	65 722	65 722	0 %	65 728	0 %	65 732	0 %	65 739	0 %	65 739	0 %
60 %	40 647	40 647	40 647	0 %	40 647	0 %	40 647	0 %	40 647	0 %	40 647	0 %
50 %	26 612	26 612	26 612	0 %	26 612	0 %	26 612	0 %	26 612	0 %	26 614	0 %
40 %	16 822	16 822	16 822	0 %	16 822	0 %	16 822	0 %	16 822	0 %	16 822	0 %
30 %	10 481	10 481	10 481	0 %	10 481	0 %	10 481	0 %	10 481	0 %	10 481	0 %
20 %	5 828	5 828	5 828	0 %	5 828	0 %	5 828	0 %	5 828	0 %	5 828	0 %
10 %	2 368	2 368	2 368	0 %	2 368	0 %	2 368	0 %	2 368	0 %	2 368	0 %

Table 3.18: *Estimated losses probability distribution — Portugal*

PT	No contagion	Base scenario	+20 % zeros		+35 % zeros		+50 % zeros		+65 % zeros		+80 % zeros	
			Average	Standard error %	Average	Standard error %	Average	Standard error %	Average	Standard error %	Average	Standard error %
90 %	1 731 395	2 465 932	2 469 978	0%	2 466 611	1%	2 496 896	1%	2 519 816	2%	2 593 774	5%
80 %	567 998	866 993	862 903	1%	856 110	3%	877 474	2%	895 202	4%	964 488	13%
70 %	196 915	274 012	272 333	1%	268 626	4%	270 659	3%	268 213	3%	268 228	5%
60 %	85 532	96 355	96 196	0%	96 170	1%	95 781	1%	95 759	2%	94 690	1%
50 %	42 275	44 584	44 569	0%	44 629	1%	44 438	0%	44 615	2%	44 240	1%
40 %	22 892	23 454	23 463	0%	23 507	1%	23 436	0%	23 518	1%	23 367	0%
30 %	12 956	13 306	13 283	0%	13 263	1%	13 219	0%	13 252	1%	13 160	0%
20 %	6 778	6 833	6 830	0%	6 833	0%	6 825	0%	6 835	0%	6 813	0%
10 %	2 933	2 942	2 942	0%	2 944	0%	2 943	0%	2 948	0%	2 942	0%