



## **Possible models for risk-based contributions to EU**

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# Possible models for risk-based contributions to EU Deposit Guarantee Schemes

European Commission, Joint Research Centre  
Econometrics and Applied Statistics Unit

This report neither commits the Commission nor limits the Commission's discretion with regard to any current or future action or policy.

## Executive summary

The investigation of risk-based models for computing contributions of Deposit Guarantee Scheme (DGS) members has become a crucial goal for the European Commission (EC) as the global crisis hits the banking sector all over the world. The new Article 12 of Directive 94/19/EC on DGS<sup>1</sup> explicitly calls for possible models for introducing risk-based contributions and requires the Commission to submit to the European Parliament and to the Council a report on the topic by the end of 2009.

The EC Joint Research Centre (JRC), in close cooperation with the European Forum of Deposit Insurers (EFDI), has investigated potential models and assessed their potential impact across Member States (MS). The present report illustrates three possible approaches for calculating contributions on the basis of the risk profile of the DGS members (i.e. banks).

The first two models are based on approaches currently applied by some of the DGS in the EU and rely on the use of accounting-based indicators to assess the risk profile of the DGS members. More precisely, 8 indicators are proposed for the first two models, covering 4 key areas (risk classes) commonly used to evaluate the financial soundness of a bank: capital adequacy, asset quality, profitability, and liquidity. All existing DGS that adjust contributions according to the riskiness of banks use accounting-based indicators.

The first model (the 'Single Indicator Model') uses a single accounting-based indicator from these risk classes (e.g. a capital adequacy indicator such as the Tier I capital ratio defined in the Basel II framework). Contributions are determined as a fixed percentage of a contribution base and subsequently adjusted by a risk factor specific to each DGS member. The fixed percentage is a political decision depending for instance on the overall amount of contributions the DGS would like to collect. The risk adjustment factor is a percentage used to increase the contributions for risky members and to decrease them for well-behaving banks.

The second model (herein identified as the 'Multiple Indicators Model') aggregates information from 4 indicators, one from each of the 4 risk classes mentioned above, to choose the adjustment coefficient. In the present study equal weight is assigned to each indicator; however, this assumption could be relaxed in the case of DGS covering a particular sector of the banking system, e.g. schemes covering cooperative or savings banks. Also, in contrast to the first model, the overall amount of contributions to be collected is set in advance and then apportioned among the DGS members depending on their risk profile.

It must be remarked that the backward-looking nature of accounting-based indicators is a common drawback of the first two models. This could be overcome by using the third model (the 'Default Risk Model'), which is more sophisticated from a mathematical point of view, and aims to estimate the probability of default of member institutions by including forward-looking information (i.e. market price information). This estimate then serves as the basis for calculating the contribution of a bank. In practical terms, the lack of market price information for many DGS members across EU MS (i.e. for those that are not listed on a stock exchange) makes the third model very difficult to implement. Presenting this approach therefore serves to set the bases for future research rather than offering a real alternative.

Numerical experiments thus focus on the first two models and compare estimated current contributions paid by a sample of banks in certain EU Member States (MS) with estimated risk-based contributions. Although the sample of banks used for the

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<sup>1</sup> Directive 94/19/EC of the European Parliament and of the Council on deposit-guarantee schemes, as amended by Directive 2009/14/EC.

experiments only covers a small subset of the entire banking system of the respective MS, evidence clearly points to an advantage for the second model.

The Single Indicator Model is tested using each of the 8 proposed indicators. Results show that focusing on a single indicator would ignore valuable information on the risk profile of the bank that is captured by other indicators which are not used. In fact, the impact on current contributions would be very different depending on the indicator selected. For this model, the EU average maximum decrease in contributions for a single bank would be 19.6 %, while the EU average maximum increase in contributions would be 27.8 %, which is a very wide range.

The Multiple Indicators Model overcomes these drawbacks. Since it takes into account information from different risk classes, the model better captures a bank's overall risk. Numerical experiments are performed using two sets of four indicators to test the change in contributions arising from the adoption of this model. Results show that the variability of the impact on current contributions is significantly reduced: the EU average maximum decrease/increase in contributions are -4.1 % and +3.8 % respectively. It is also found that changing the set of indicators does not have much influence. This model thus seems the best option.

A certain number of choices had to be made to conduct the experiments for both models. These mainly cover how risk ratings are assigned to banks, and how differences in risk profiles should be reflected in terms of contributions. These choices can in practice differ for different DGS, depending for instance on the MS banking system, on the specific banking sector covered by a DGS and, more generally, on the behaviour of financial markets as a whole.

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# 1. Introduction

During the 2006 review of Directive 94/19/EC on Deposit Guarantee Schemes (DGS), the EC put forward the possibility of introducing, on a voluntary basis, risk-based contributions in EU DGS<sup>2</sup>. This issue became more prominent in the light of the Directive amendment, which represents the EC answer to the financial crisis. Under Article 12 of the Directive amendment, the EC is to submit by the end of 2009 a report covering different issues related to the new rules on DGS, with special reference to possible models for risk-based contributions to DGS.

Following a request by the EC Directorate-General for Internal Market and Services (DG MARKT), the Joint Research Centre (JRC) has been in charge of investigating potential models for risk-based contributions. Representing 38 out of the 39 EU DGS, the European Forum of Deposit Insurers<sup>3</sup> (EFDI) was asked to assist the JRC in addressing this task.

The JRC organised the work in three stages:

- 1) Investigation of the risk-based models currently applied across EU countries
- 2) Model proposal
- 3) Numerical exercises on the model proposal.

The 2008 JRC report 'Risk-based contributions in EU Deposit Guarantee Schemes: current practices'<sup>4</sup> covered the first stage of the project and was intended to lay the foundations for developments on the subject. The present report covers the last two stages of the project.

The aim of the 2008 JRC report was twofold: first, to illustrate systems currently applied across the EU and highlight the fundamental principles underlying risk determination; second, to provide more technical details of each method, including a description of the mathematical tools employed. Although, as a matter of fact, each risk-based DGS has put into force a unique and peculiar system, accounting-based indicators are always applied to measure the risk of the DGS members. The indicators are used to classify members into rating classes which are then used to increase or decrease members' contributions, depending on the riskiness of each member.

Having clarified that the present report rests on the foundations established by the previous one, the goal is to suggest common risk-based approaches that could be implemented, on a voluntary basis, by EU DGS. The proposed models are constructed starting from some approaches applied in some EU MS and taking into account the contribution of the Working Group on risk-based contributions set up by the EFDI (in short: EFDI WG). During the joint work with the JRC, the EFDI WG, on the basis of the experience of their members, identified the following requirements for assessing possible models:

1. SIMPLE: the model needs to be understandable by the DGS members (i.e. it must not feature complex formulas).
2. ACCURATE: the model should accurately reflect the relative risk that the DGS members pose to the DGS fund (i.e. the model should be effective at differentiating banks into appropriate risk categories).

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<sup>2</sup> Communication from the Commission to the European Parliament and the Council concerning the review of Directive 94/19/EC on Deposit Guarantee Schemes, COM(2006) 729, [http://ec.europa.eu/internal\\_market/bank/docs/guarantee/comm9419\\_en.pdf](http://ec.europa.eu/internal_market/bank/docs/guarantee/comm9419_en.pdf).

<sup>3</sup> <http://www.efdi.net/>. The JRC would like to thank the EFDI for their fruitful cooperation on this project.

<sup>4</sup> [http://ec.europa.eu/internal\\_market/bank/docs/guarantee/risk-based-report\\_en.pdf](http://ec.europa.eu/internal_market/bank/docs/guarantee/risk-based-report_en.pdf).

3. REASONABLE: in terms of the amount of information required (data gathering), the model should avoid unduly burdening DGS members.
4. AFFORDABLE/SUSTAINABLE: the model should not cause insolvency to any DGS members, i.e. the costs resulting from the model should be bearable for its members. To this end a maximum rule of some kind (e.g. concerning the amount of contribution) might be embedded in the model.
5. FLEXIBLE: the model should be adjustable to different countries, i.e. to different economies, different financial markets and/or different bank types.
6. OPEN and TRANSPARENT: the DGS members should know why they fall into one class and should be able to verify it (but any kind of 'manipulation' of the system must be avoided: members must not be allowed to take advantage by adjusting technical details).
7. EQUITABLE/IMPARTIAL: the model should be fair, i.e. banks with similar characteristics should be treated similarly.

This catalogue is rather wide, and some points of the list may clash with each other, e.g. a simple model might not be very accurate.

All risk-based systems currently applied in the EU were evaluated by the EFDI WG according to the above catalogue, trying to investigate which details and specific aspects would deserve replication and which ones should not be applied or only to a lesser extent. As a result, two models have been accepted by the EFDI WG as sufficiently fulfilling the above list of criteria. In both models the risk-based component is built using accounting data. They are explained in detail and have been tested on a sample of banks from MS. A third model, more sophisticated from a mathematical point of view, is also briefly discussed. In addition to accounting data, this model also relies on market price information.

The first model replicates the minimum common framework identified by the 2008 JRC report: contributions are defined as a fixed percentage of the contribution base (in general the amount of eligible or covered deposits of the members); for each member, the obtained value is then multiplied by a factor reflecting the bank's risk profile. In this approach, only one indicator is considered. The fixed percentage is chosen by the DGS in order to reflect the total amount of contributions to be collected in a year and can for instance be linked to a target size for the DGS funds.

The second model is based on a mixture of indicators belonging to the classes identified in the 2008 JRC report: capital adequacy, asset quality, profitability, and liquidity. Indicators have been chosen with the help of the EFDI WG. This approach aims to unify the two most complex systems currently in use (Italy and France), reducing technicalities in order to make the model adjustable to different banking systems. The model is built so that the overall amount of contribution is decided *a priori* and then apportioned among the DGS members depending on their risk. The apportionment of contributions is geared to fulfilling the above list of requirements.

It must be stressed that both proposals discussed above resort to internal thresholds to classify members into rating classes. Since pre-specified values for the thresholds do not seem to be adequate to cope with different banking systems and banking legislations, it could be suggested that rating classes be built using the quantiles of the distributions of the

chosen indicators<sup>5</sup>. This would take into account the potentially different characteristics of the banking sector in different EU MS and would make the models very flexible (which is one key requirement). The use of quantiles also partially mitigates procyclical effects<sup>6</sup>. By using quantiles, the contribution of a given bank is defined in relative terms with respect to the other banks. Thus an increase in the risk of a bank during a period of financial stress would impact on its contributions only if the risk indicators of all other DGS members remained unchanged. However, it can be assumed that the risk indicators of all DGS members will be affected to a certain extent during a period of financial stress<sup>7</sup>.

The last model is mathematically more sophisticated: the debate on the subject has grown during the last decades and academic research has proposed a large number of models to address the issue of how to incorporate risk-based information. In this more academically oriented stream, we propose a cornerstone of financial modelling, by adapting the Merton model<sup>8</sup> to the DGS framework. Contributions under this model are dependent on the banks' estimated 'probability of default'. The closer a bank is to a default situation, the more it will have to contribute.

Table 1 gives an overview of the three different models considered, highlighting the main differences between them.

**Table 1: Main characteristics of the three models.**

	Risk base component	Type of data model relies on
'Single Indicator Model'	1 indicator (financial ratio)	Financial statements
'Multiple Indicators Model'	Multiple indicators (financial ratios)	Financial statements
'Default Risk Model'	'Default probability'	Financial statements + market prices

The numerical experiments, presented in the last part of the report, focus on the first two models, since the third one relies on the use of market price information that is not available for many DGS members. Estimated contributions currently paid to DGS by a subset of banks across the EU are compared with contributions that would arise from the application of the two approaches. The aim of the experiment is to highlight the main differences between the two models and give a first insight into the impact these approaches would have on EU banking systems.

<sup>5</sup> A quantile is the value of a variable below which a certain percentage of observations fall. So the 20th percentile is the value (or score) below which 20 per cent of the observations may be found.

<sup>6</sup> 'The term pro-cyclicality refers to the dynamic interactions (positive feedback mechanisms) between the financial and the real sectors of the economy. These mutually reinforcing interactions tend to amplify business cycle fluctuations and cause or exacerbate financial instability.' Report of the Financial Stability Forum on Addressing Procyclicality in the Financial System, April 2009, Financial Stability Forum, [http://www.financialstabilityboard.org/publications/r\\_0904a.pdf](http://www.financialstabilityboard.org/publications/r_0904a.pdf).

<sup>7</sup> To understand whether the two model proposals suffer from a pro-cyclicality effect, the risk of a given member could be decomposed into a systemic component (i.e. one that is equal for all banks and depends on the economic cycle) and a specific component (i.e. peculiar to each individual bank). By using quantiles, the effect of the systemic component is completely eliminated.

<sup>8</sup> The Merton model is a credit risk model defining a default event for a bank in terms of the bank's asset value (i.e. its market value). The asset value is treated stochastically and default occurs if the asset value process is lower than the value of the bank's liabilities. More details are provided in Section 3.3.

The remainder of the report is organised as follows: Section 2 focuses on the choice of the indicators used in the models, while Section 3 presents the three models; Section 4 illustrates the results of the numerical experiments performed to investigate the first two models. The last section puts forward some conclusions.

Six technical Annexes are also included: Annex I overviews the funding mechanisms adopted by EU MS as of 01/01/2008. Annex II describes the procedure used to estimate the contribution base for the set of banks in the numerical experiment. The last four annexes present numerical results of the Single Indicator Model and the Multiple Indicators Model on a country-by-country basis.

A number of assumptions had to be made to conduct the experiments. These mainly covered how risk ratings are assigned to banks, and how differences in risk profiles should be reflected in terms of contributions.

## 2. Choice of indicators

As already outlined, a wide variety of indicators have been considered, tested and applied by EU schemes. These indicators are often based on banks' financial statements. A significant effort has been put (also by the EFDI WG) into identifying the indicators to be applied in the model proposals. As a result, we propose a couple of indicators for each of the key areas that are commonly used to assess the financial soundness of a bank: capital adequacy, asset quality, profitability, and liquidity. These 4 categories are among the evaluation factors considered under the widely used CAMELS rating approach. Under this approach, the performance of banks is measured using the following six evaluation factors: Capital adequacy, Asset quality, Management quality, Earnings ability/profitability, Liquidity and Sensitivity to market risk. Out of these six factors we will only consider those that can be easily quantified using financial statements data. The indicators proposed for each of the 4 categories selected are listed in Table 2.

- **Capital adequacy.** The purpose of a bank's capital is to act as a buffer to absorb unexpected losses and shocks. The ratio of a bank's capital to its risk-adjusted assets is the most often used measure of a bank's capital adequacy. All other things being equal, the riskier the assets of a bank are, the bigger the capital should be to reach the same capital adequacy ratio. The two ratios proposed in Table 2 differ solely by the categories of capital that are covered. In the Tier 1 ratio, only Tier 1 capital (i.e. mainly shareholder's equity) is considered. The total capital ratio (or capital adequacy ratio under the Basel rules) covers Tier 1 and Tier 2 capital. Tier 2 capital includes certain subordinated debt, hybrid capital, loan loss reserves and valuation reserves.
- **Asset quality.** Claims resulting from loans are often the largest asset class for a bank. Hence the importance of assessing the quality of the bank's loan portfolio. The first proposed indicator, the Non Performing Loans ratio, measures the proportion of the total amount of loans that can be considered doubtful, as a result of the borrower failing to repay on time or the full amount after a certain period (e.g. 3 months). The second indicator relates the risk and the return in the loans portfolio of a bank, by looking at the relationship between the provisions set aside for expected loan losses and the interest income over the same period. Ideally this ratio should be as low as possible. If a bank with a high risk portfolio of loans (i.e. setting aside a significant proportion of provisions) is well managed, this should be reflected by high interest margins.
- **Profitability.** The purpose of profitability indicators is to measure the capacity of a bank to generate earnings. This will in turn influence the bank's ability to, for instance, increase its capital, cover future losses, increase its assets or provide a dividend to its shareholders. The first proposed indicator, cost to income ratio, measures the size of the bank's operating costs as a proportion of its operating income. The second indicator (and the most widely used), return on average assets, looks at the profitability generated by the bank's assets.
- **Liquidity.** The purpose of liquidity indicators is to measure to what extent a bank can pay obligations falling due and fund new business. The first proposed indicator, the liquid assets to deposits ratio, measures the percentage of the customers and short-term funding that could be paid from the proceeds of liquid assets in the event of a sudden withdrawal of funds. Another source of potential liquidity risk (as well as interest rate risk) for a bank is the maturity mismatch between its assets and its liabilities (i.e. long-term loans are granted using short-term deposits). The second indicator, the loan to deposit ratio, is used for this purpose. The higher the ratio, the bigger the risk.

Table 2: List of indicators applied in the proposed models.

Class	Name	Abbreviation	Formula
Capital adequacy	Tier 1 capital ratio	CA1	$\frac{\text{Tier I Capital}}{\text{Risk weighted assets}}$
	Total capital ratio	CA2	$\frac{\text{Total Capital}}{\text{Risk weighted assets}}$
Asset quality	Non Performing Loan (NPL) ratio	AQ1	$\frac{\text{Non Performing Loans}}{\text{Gross Loans}}$
	Loan loss provision	AQ2	$\frac{\text{Loan Loss Provision}}{\text{Net Interest Revenue}}$
Profitability	Cost to income ratio	P1	$\frac{\text{Operating Expenses}}{\text{Operating income}}$
	Return on average assets (ROA)	P2	$\frac{\text{Net Income}}{\text{Average Total Assets}}$
Liquidity	Liquid assets to deposits ratio	L1	$\frac{\text{Liquid Assets}}{\text{Customer \& Short Term Funding}}$
	Loan to deposit ratio	L2	$\frac{\text{Net Loans}}{\text{Customer \& Short Term Funding}}$

### 3. Model proposals

#### 3.1 Single Indicator Model

Although there is no harmonised approach among EU DGS towards risk-based methods currently applied to compute members' contributions, a minimum common framework was identified and discussed in the 2008 Report, leading to this 'basic' proposal. With the aim of keeping the burden of computing contributions as limited as possible, the model is based on the use of a single indicator.

The most common risk-based approach is to define members' contributions as the product of a contribution base,  $x_i$  (generally the total amount of eligible or covered deposits), increased or decreased by a percentage  $\beta_i$  proportional to the risk attitude of the  $i$ -th member and a percentage,  $\alpha$ , common to all members, reflecting the overall conditions in the banking system in the country. In formula, the contribution  $c_i$  is expressed as follows:

$$\text{Error! Objects cannot be created from editing field codes.} \quad (1)$$

In operative terms, the coefficient  $\alpha$  is often set in the statutes (or by-laws) regulating the DGS and/or revised on a regular basis by the board of the scheme. For instance, it can reflect improvements or deteriorations in the soundness of the national banking sector and, consequently, leads to an increase or decrease in the total amount of resources collected. Alternatively,  $\alpha$  could be connected to a technical procedure identifying the target size of the fund or to a mechanism forecasting the future funding need of the DGS.

Coefficient  $\beta_i$  explicitly takes into account the riskiness of the DGS members: a lower risk leads to a lower contribution and a higher risk to a higher one. In this basic proposal,  $\beta_i$  can vary between 80% (for the least risky banks) and 150% (for the most risky banks) and is determined using one of the indicators listed in Table 2.

The coefficient  $\beta_i$  to be applied to each member relies on their classification into rating classes defined in terms of the distribution of the ratios of the DGS members. Thresholds for classifying members are defined in terms of the quantiles<sup>9</sup> of the ratio distribution, as shown in Table 3. This means that the range of values of the indicators of the banks in a country is taken into account to assign the  $\beta_i$  coefficients. As an illustration, Figure 1 provides the density distribution of the CA1 ratio for a sample of banks<sup>10</sup> in the EU-27 as of 31 December 2007: banks with a high value of the ratio (i.e. less risky banks) fall in the right tail of the distribution, while more risky banks fall in the left part of the curve. Dotted lines represent the quantiles listed in Table 3.

Table 3: Single Indicator Model: relationship between the quantiles of the distribution of the capital adequacy ratio and the coefficient  $\beta_i$  to compute risk-based contributions.

Capital adequacy indicator quantiles ( $q_p$ )	$\beta_i^{(q)}$
0 to 10 (most risky)	150 %
10 to 25	125 %
25 to 40	100 %

<sup>9</sup> For a definition see footnote 5 above.

<sup>10</sup> More details on the sample can be found in Section 4.

40 to 60	90%
60 to 100 (least risky)	80%

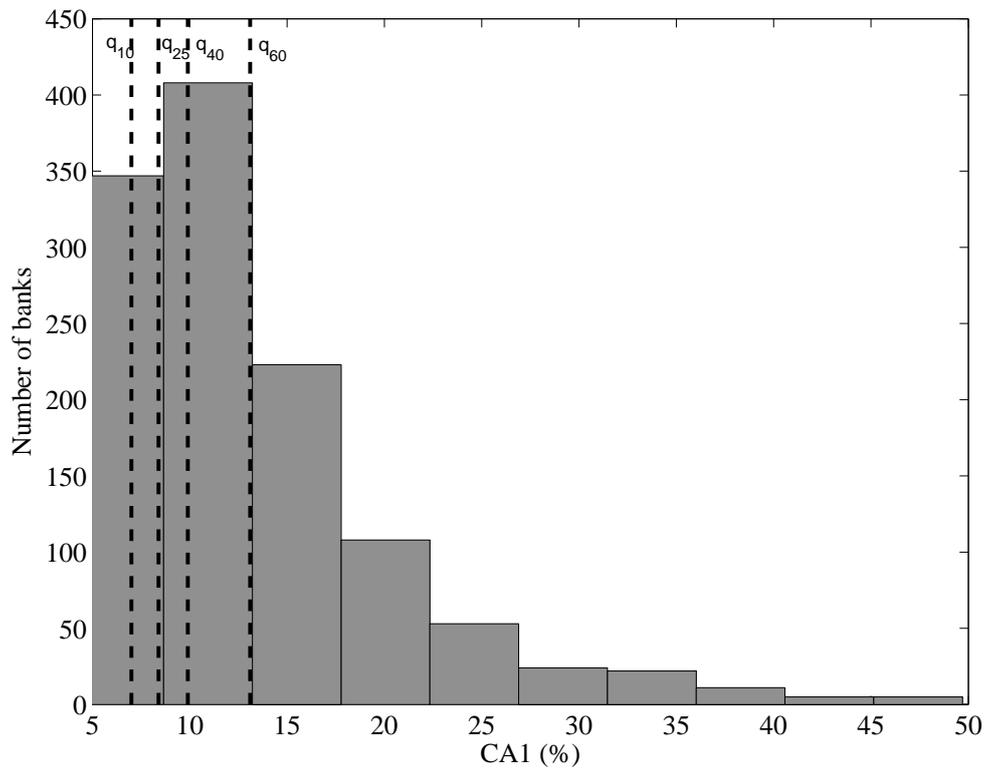


Figure 1: CA1 distribution for a sample of banks in the EU-27 as of 31 December 2007. The vertical lines represent the quantiles of the distribution listed in Table 3. CA1 source: Bankscope™.

All the members with a ratio lying below quantiles  $q_p$  will be assigned the corresponding coefficient  $\beta_i^{(q)}$ . For instance, pointing to Figure 1, a bank with a CA1 equal to 12% (i.e. lying between the 40th and the 60th quantile ( $q_{40}$  and  $q_{60}$  respectively)) will be assigned the coefficient 90%.

This model shows a great degree of flexibility:

- 1) the thresholds proposed above — both chosen quantiles and corresponding beta values — are arbitrary and can be adapted for instance by taking into account the characteristics of the banking system of a country;
- 2) the value of coefficient  $\alpha$ , equal for all members, reflects a political decision on the strength of the ex-ante component of the DGS funding and can lead to a narrower or wider range of variation for the members' contribution. In Figure 2, an example is provided describing three possible choices for coefficient  $\alpha$ , namely  $\alpha = 0.5\%$  (low ex-ante funding),  $\alpha = 1\%$  (medium ex-ante funding), and  $\alpha = 2\%$  (high ex-ante funding). Following Table 3, the minimum and maximum values for  $\beta_i$  are respectively 80% and 150%. For instance, when considering a value for  $\alpha$  equal to 1%, contributions could vary between 0.8% (obtained as 1% multiplied by the minimum value for  $\beta_i$  equal to 80%) and 1.5% (obtained as 1% multiplied by the maximum value for  $\beta_i$  equal to 150%).

There are three main drawbacks in the model just presented: first, it relies on the use of a single indicator describing the risk profile; second, the aggregated amount of contributions collected by the DGS is not known *a priori* since it depends on the

position of the members within the distribution of the ratio; third, it relies on accounting data and thus is not forward-looking in nature.

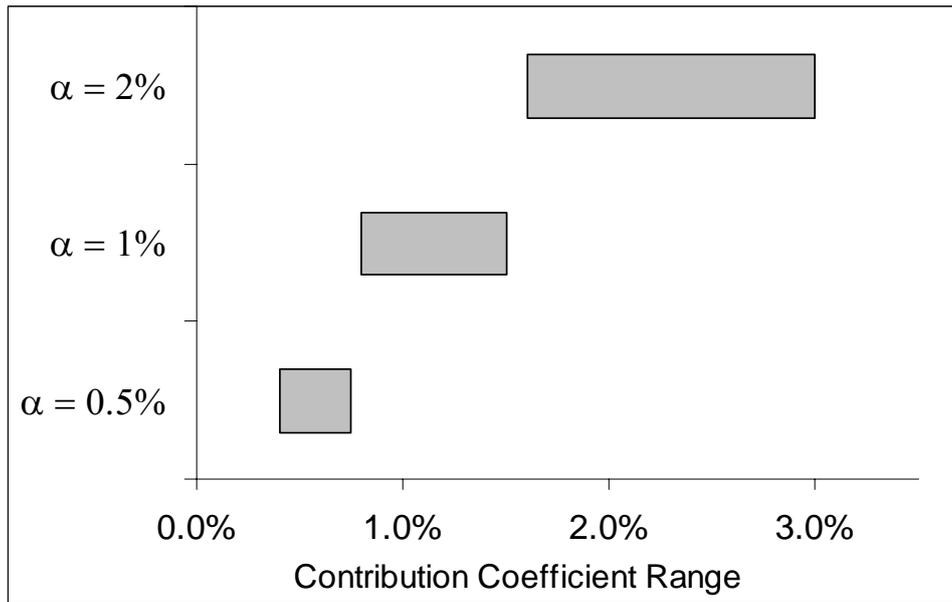


Figure 2: Single Indicator Model: range of variation of the contribution coefficient depending on the choice of  $\alpha$ . The risk-based correction  $\beta$  varies between 80% and 150%.

## 3.2 Multiple Indicators Model

A multiple indicators approach is clearly more complex, since it aims to overcome the main drawback of the Single Indicator Model, namely the fact that it relies on only one indicator.

The Multiple Indicators Model is based on the assumption that the total amount of contributions collected by the scheme needs to be decided *a priori* (e.g. by the DGS board or the government) and then apportioned among members. The members' contributions are calculated by multiplying the total amount of contributions (TC) to be collected by the scheme by a coefficient which will be labelled as Risk Share (RS) since it represents the relative risk weight of each member. In formula the contribution  $c_i$  for the  $i$ -th member can be expressed as follows:

$$c_i = TC \cdot RS_i. \quad (2)$$

The set of weights  $RS_i$  is obtained by combining the contribution base of the members and their risk behaviour, as follows (see also Figure 3):

- 1) The overall risk behaviour of each member is described by a coefficient  $\beta_i$  determined by combining the information given by 4 indicators, one for each class described in Section 2<sup>11</sup>. Each member is assigned a score depending on the values of the 4 indicators and the scores are subsequently translated into  $\beta_i$  via a linear relationship, as specified below.
- 2) For each member the risk amount is obtained by multiplying  $\beta_i$  by its contribution base  $x_i$ , represented by the amount of eligible or covered deposits:

$$RA_i = x_i \cdot \beta_i. \quad (3)$$

The risk amount represents the DGS exposure towards one member, corrected by the risk coefficient of the member itself.

- 3) The risk share of each member is obtained by normalised risk amounts:

$$RS_i = \frac{RA_i}{\sum_{j=1}^N RA_j} \quad (4)$$

where  $j$  sums up all the  $N$  credit institutions members of the DGS.

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<sup>11</sup> Combinations of more than four indicators can also be considered.

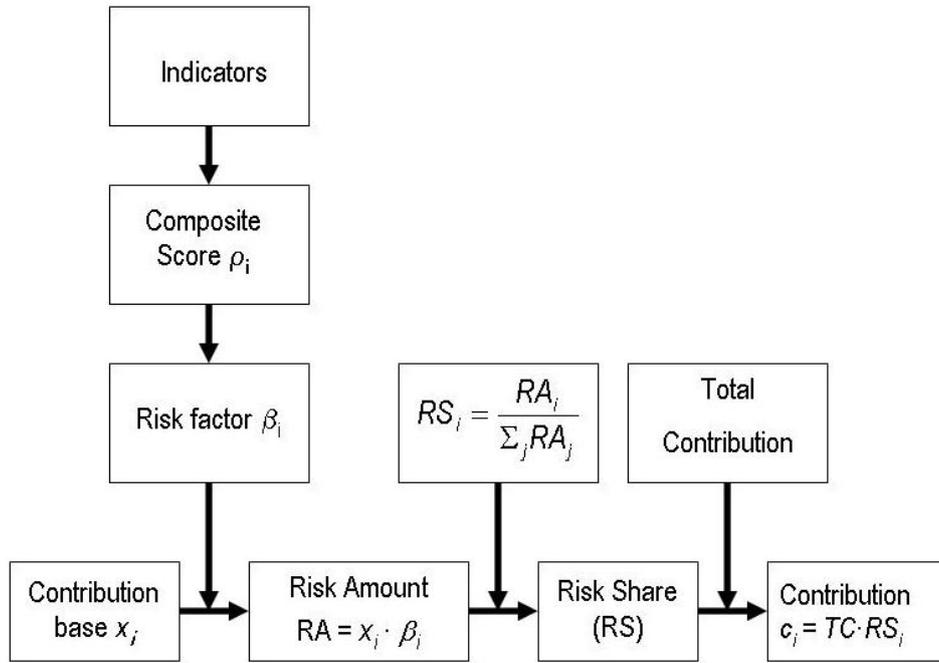


Figure 3: Calculation procedure for Multiple Indicators Model.

As for the basic approach, the risk factor  $\beta_i$  is allowed to vary between 80% and 150% and is calculated by means of a linear transformation (see Figure 4) of another variable,  $\rho_i$  assessing the overall behaviour of the DGS members based on a set of indicators.

In detail, the variable  $\rho_i$  which will be referred to as the *composite score*, is defined as the average of 4 scores, each covering a different aspect of DGS members' behaviour:

$$\rho_i = \frac{1}{4} \left[ \rho_i^{(1)} + \rho_i^{(2)} + \rho_i^{(3)} + \rho_i^{(4)} \right].$$

Each  $\rho_i^{(j)}$  (with  $j = 1, 2, 3, 4$ ) is a score built to indicate the risk of the DGS members: the higher the score, the higher the risk. More specifically,  $\rho_i^{(1)}$  is a capital adequacy score,  $\rho_i^{(2)}$  is an asset quality score,  $\rho_i^{(3)}$  is a profitability score, and  $\rho_i^{(4)}$  is a liquidity score. A possible choice for the scores to be assigned is shown in Table 4. For all classes, scores range from a minimum score of 1 describing a 'very low risk' situation, to a maximum score of 5 to indicate a 'very high risk' situation. Being the simple average of 4 scores taking values between 1 and 5, the composite score will also vary between the same limits. As in the Single Indicator Model, scores to discriminate among DGS members are obtained using the quantiles of the distribution of the indicators. Table 5 lists a proposed set of quantile thresholds in order to assign scores for each of the eight indicators.

Table 4: Scores to be assigned to the DGS members, based on the set of indicators.

Class	Capital adequacy	Asset quality	Profitability	Liquidity
Very low risk	1	1	1	1
Low risk	2	2	2	2
Medium risk	3	3	3	3

High risk	4	4	4	4
Very high risk	5	5	5	5

Table 5: Thresholds for the 8 indicators used to assess the risk of members.

Risk class	Ratio	Scores				
		$\rho_i^{(j)}=1$	$\rho_i^{(j)}=2$	$\rho_i^{(j)}=3$	$\rho_i^{(j)}=4$	$\rho_i^{(j)}=5$
Capital adequacy	Tier 1 capital ratio	Quantiles 60 to 100	Quantiles 40 to 60	Quantiles 25 to 40	Quantiles 10 to 25	Quantiles 0 to 10
	Total capital ratio	Quantiles 60 to 100	Quantiles 40 to 60	Quantiles 25 to 40	Quantiles 10 to 25	Quantiles 0 to 10
Asset quality	NPL ratio	Quantiles 0 to 20	Quantiles 20 to 40	Quantiles 40 to 60	Quantiles 60 to 80	Quantiles 80 to 100
	Loan loss provision	Quantiles 0 to 20	Quantiles 20 to 40	Quantiles 40 to 60	Quantiles 60 to 80	Quantiles 80 to 100
Profitability	Cost to income ratio	Quantiles 0 to 20	Quantiles 20 to 40	Quantiles 40 to 60	Quantiles 60 to 80	Quantiles 80 to 100
	Return on average assets	Quantiles 80 to 100	Quantiles 60 to 80	Quantiles 40 to 60	Quantiles 20 to 40	Quantiles 0 to 20
Liquidity	Liquid assets to deposits ratio	Quantiles 80 to 100	Quantiles 60 to 80	Quantiles 40 to 60	Quantiles 20 to 40	Quantiles 0 to 20
	Loan to deposit ratio	Quantiles 0 to 20	Quantiles 20 to 40	Quantiles 40 to 60	Quantiles 60 to 80	Quantiles 80 to 100

For instance, let us consider the following set of four indicators: CA1, AQ1, P1 and L1; suppose that the indicators for a bank all lie between the 40th and 60th quantiles of the corresponding distribution. Following Table 5 the scores for this bank will be:  $\rho_i^{(1)}=2$ ,  $\rho_i^{(2)}=3$ ,  $\rho_i^{(3)}=3$ , and  $\rho_i^{(4)}=3$ . And the composite score will thus be  $\rho_i = \frac{1}{4}[2 + 3 + 3 + 3] = 2.75$

In practice, each scheme could adapt Table 4 and Table 5 according the specific situation of the national banking sector or following the particular needs of each DGS. For instance, if a MS wished to give more weight to the CA indicator, the scores for that class could be doubled.

The set of composite scores of the members are used to obtain the risk adjustment ( $\beta_i$ ) by means of a linear transformation, as shown in Figure 4. The mechanism functions as follows: taking the value of 80% for  $\rho_i=1$  and the final value of 150% for  $\rho_i = 5$  as starting points, all the members are assigned the resulting  $\beta_i$  values depending directly (that is, linearly) on their relative values of the composite score  $\rho_i$ .

By introducing this linearisation as a last step, the contributions for members with very close values for the composite indicator will be very similar. Referring to the list of desired characteristics in Section 1, this procedure makes the model much more impartial than using classes for the final risk correction, since members with very close values of the aggregated indicator could fall into different classes.

Note that, as in the case of the Single Indicator Model, the choice of the scores and quantiles reported in Table 4 and Table 5 is arbitrary and could be potentially adjusted in any MS. Moreover, Table 4 shows that equal importance is assigned to any indicator since the scores are the same. This assumption could be relaxed too if, for instance, the DGS members represent a specific sector of the banking system. By way of example, if the DGS members are only cooperative or savings banks<sup>12</sup>, it could be suggested that the profitability indicator be weighted more and the asset quality indicator less.

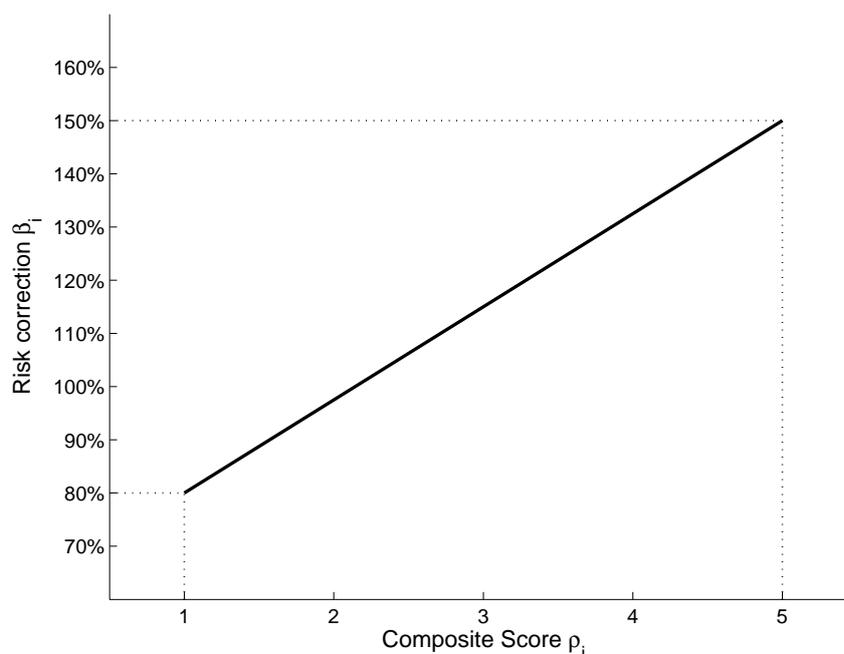


Figure 4: Multiple Indicators Model: linear transformation used in order to obtain the risk correction  $\beta_i$  from the composite score  $\rho_i$ .

<sup>12</sup> This is the case for some EU DGS in AT, ES, IT, PT.

### 3.3 Default Risk Model

A different approach to compute risk-based contributions is to use credit risk models. The main output of a credit risk model is the probability density function of the loss of a credit portfolio, i.e. a measure of the probability that losses of a certain size will occur. Credit risk models are developed mainly to evaluate the risk exposure of banks dealing with a portfolio of loans. However, they can be used in the framework of protection schemes if a DGS is thought of as holding a portfolio of creditors represented by its members. Banks are exposed to the possibility that their debtors will default and will not be able to honour their obligations, i.e. repay the money back; the DGS is exposed to the possibility that a bank will go bankrupt and will not be able to pay out depositors.

Due to the mathematical complexity of these models and to the fact that they rely not only on accounting data but also on market data (i.e. data on equity prices), their application at DGS level is not currently recommended. Therefore, the remainder of this section serves as an illustration, setting the bases for future research, rather than as a real alternative.

Starting from the option pricing theory originally proposed by Black and Scholes<sup>13</sup> and Merton<sup>14</sup>, it is possible to price the cost of deposit insurance by a third party<sup>15</sup>, such as by a DGS. The option pricing theory is well recognised among experts in the field of mathematical modelling and, above all, is acknowledged as a classical and relevant source.

The idea of this approach is to describe the default risk of an individual bank by a default process. In the Merton model the default process of a company is driven by the value of the company's assets and the risk of a firm's default is therefore explicitly linked to the variability in the firm's asset value. The basic intuition behind the Merton model applied in the framework of deposit insurance is the following: the default of a bank occurs when the market value of the bank's assets falls below a certain threshold, which is determined by the value of the bank's liabilities. Figure 5 presents an example with two different scenarios for the evolution of the asset value of a bank over a time period of 9 years. The dash-dotted line represents the value of the bank's liabilities. The solid line represents the case where the bank defaults since it falls below the value of liabilities; if the bank's asset value follows the dotted line, the bank does not default.

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<sup>13</sup> Black, F., and Scholes, M., 'The valuation of options and corporate liabilities', *Journal of Political Economy*, 1973, 81, 637-659.

<sup>14</sup> Merton, R., 'Theory of Rational Option Pricing', *Bell Journal of Economics and Management Science*, 1973, 4(1), 141-183.

<sup>15</sup> Merton, R., 'An Analytic Derivation of the Cost of Loan Guarantees and Deposit Insurance: An Application of Modern Option Pricing Theory', *Journal of Banking and Finance*, 1977, 1, 3-11.

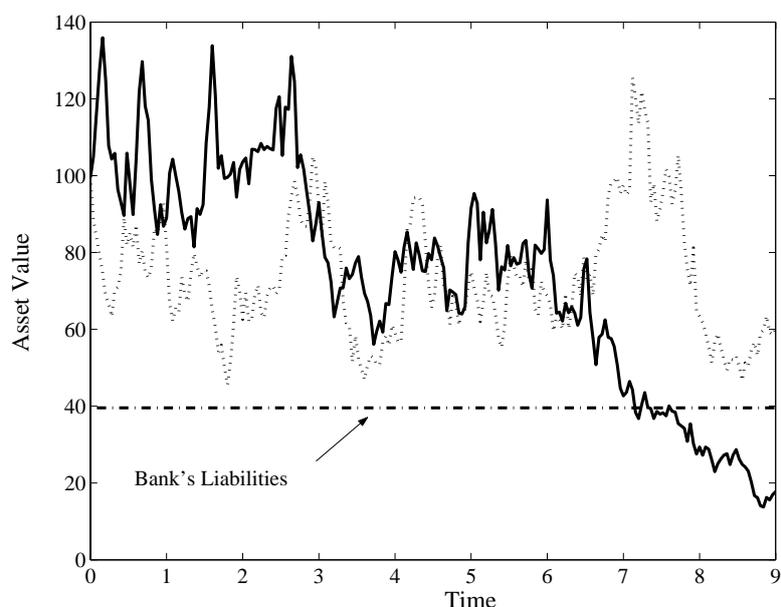


Figure 5: Simulated paths for the asset value of a bank: the solid line and dash-dotted line represent respectively a default and non-default situation.

Starting from a modified version of the Merton model developed by KMV<sup>TM16</sup>, Sironi and Zazzara<sup>17</sup> show how to estimate both individual and portfolio default risks and evaluate the adequacy of the Italian Deposit Insurance Fund (Fondo Interbancario di Tutela dei Depositi)<sup>18</sup>. In the paper the default probability of a bank at a certain point in time is derived by measuring the so-called *distance to default*, i.e. the number of standard deviations the asset value is away from the default threshold. In formula:

$$Distance\ to\ Default = \frac{Asset\ Value - Default\ Point}{Asset\ Value \times Asset\ Volatility}$$

The default probability is obtained by converting the distance to default using data on historical defaults and bankruptcy frequencies. Note that a problem may arise at this last step given the limited number of bank default events, which makes it difficult to construct a large enough data set. Approaches such as the one by KMV<sup>TM</sup> make use of a US system dataset collected during the Saving and Loans crisis and containing a considerable number of bank defaults. It must be stressed that this database might contain information not applicable to most of the banking system in the EU MS.

Finally, the paper shows how to estimate the marginal contribution of an individual insured bank to the DGS portfolio risk. This measure, which depends upon a bank's default probability, could be used to apportion annual DGS fees among DGS members.

<sup>16</sup> Crosbie, P., 'Modeling default risk', 2003, Moody's-KMV<sup>TM</sup>. KMV is an acronym representing the names of the founders of Moody's (S. Kealhofer, J. McQuown and O. Vasicek), one of the world's leading providers of credit risk quantitative solutions. <http://www.moodyskmv.com>.

<sup>17</sup> Sironi A., and Zazzara C., 'Applying Credit Risk Models to Deposit Insurance Pricing: Empirical Evidence from the Italian Banking System', *Journal of International Banking Regulation*, 2004, 6(1), 10-32.

<sup>18</sup> Note that the Italian DGS is ex-post funded but Article 21 of the Statute of the scheme sets up a virtual fund which the members undertake to make available if the scheme is triggered.

## 4. Numerical experiments

The purpose of this section is to provide a preliminary quantitative assessment of the impact the introduction of the first two risk-based models proposed (Single Indicator Model and Multiple Indicators Model) would have on banks. Specifically, contributions paid by banks under funding systems currently applied across MS are compared with contributions computed using the two model proposals.

Table 6: Number of banks in the sample for each EU MS.

MS marked with an asterisk indicates ex-ante and non-risk-based systems as of 01/01/2008. In MS where more than one DGS is operating, data are aggregated. Hat labelled information as of 01/01/2006.

Country	Number of banks in the sample	Number of local members in the DGS (2008)
AT	3	150
BE*	5	103
BG*	11	24
CY*	6	15
CZ*	2	38
DE	16	1229
DK*	11	199
EE*	2	6
ES*	52	197
FI	3	91
FR	21	711
GR*	11	35
HU*	3	188
IE*	8	48^
IT	573	732
LT*	8	77
LU	6	233
LV*	3	56
MT*	2	19^
NL	10	279^
PL	5	632
PT	13	150
RO*	4	33
SE	10	168
SI	5	21
SK*	4	16
UK	29	750

The data at bank level required to estimate contributions for the two model proposals is currently not available for any of the EU deposit guarantee schemes. As an alternative, we considered for each EU MS a set of banks for which the required information is accessible on databases covering banking activities. The resulting sample, composed of 826 banks, is broken down by MS as detailed in Table 6. The numerical exercise is, however, limited to the EU MS adopting an ex-ante and non-risk-based funding mechanism as of 1 January 2008, since for the other countries current contributions cannot be estimated. These MS have been marked with an asterisk in Table 6. The total number of banks in this subset of MS is 137.

Data in the table show that for many MS the sample of banks for which all the required data is available covers only a small subset of the national banking system. Since both models use the distribution of financial ratios to classify members into rating classes in order to assign risk-based coefficients to adjust contributions, working with such a small sample is not statistically correct. For this reason, when computing quantiles of the distribution of the ratios, the entire set of 826 EU banks is used for both models. It has to be specified that the distribution of the ratios in a MS can be rather different from the global EU distribution. It can also be expected that results would change when considering a different sample of banks. It can be suggested that for small banking systems numerical thresholds, possibly coming from accounting practices and reflecting national specificity, could replace the use of quantiles, which can instead be used for DGS with a large number of members.

For all these reasons, results should be read with caution and definitive conclusions cannot be drawn. The remainder of this section is organised as follows: Section 4.1 describes how the dataset was built, focusing especially on the data sources and the data needed; Section 4.2 presents the results, highlighting the pros and cons of each approach.

## 4.1 The dataset

### Data sources

The Bankscope™ database served as the main source of information to build the dataset sample<sup>19</sup>. Data from Eurostat (<http://epp.eurostat.ec.europa.eu>) and information collected by the JRC from national Deposit Guarantee Schemes were also used.

### Data requirements

As described in Sections 2 and 3, the calculation of members' contributions under the first two models (Single Indicator Model and Multiple Indicators Model) relies on:

- financial ratios calculated from financial statements data: one ratio in the case of the Single Indicator Model, and a combination of ratios for the Multiple Indicators Model. Data on the financial ratios proposed was readily available from Bankscope™;
- the contribution base, i.e. the amount of eligible or covered deposits, depending on the country (see Annex I for a short description of the funding systems adopted by EU MS). Data on the contribution base is not available in Bankscope™ since it depends on the eligibility rules in force and on the level of coverage applied by each country. For this reason the exercise relies on estimates for the banks' contribution base. Bankscope™ provides data on the total amount of deposits a bank has as a liability (i.e. from any type of customers, interbank deposits, own funds, etc.). This figure is then adjusted in a three-step process, as depicted in Figure 6, in order to obtain the total amount of eligible and covered deposits. Technical details on the adjustment procedure are given in Annex II.

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<sup>19</sup> Bankscope™ is a database provided by Bureau van Dijk Electronic Publishing (BvDEP) and contains balance sheet and income statements data for banks worldwide.

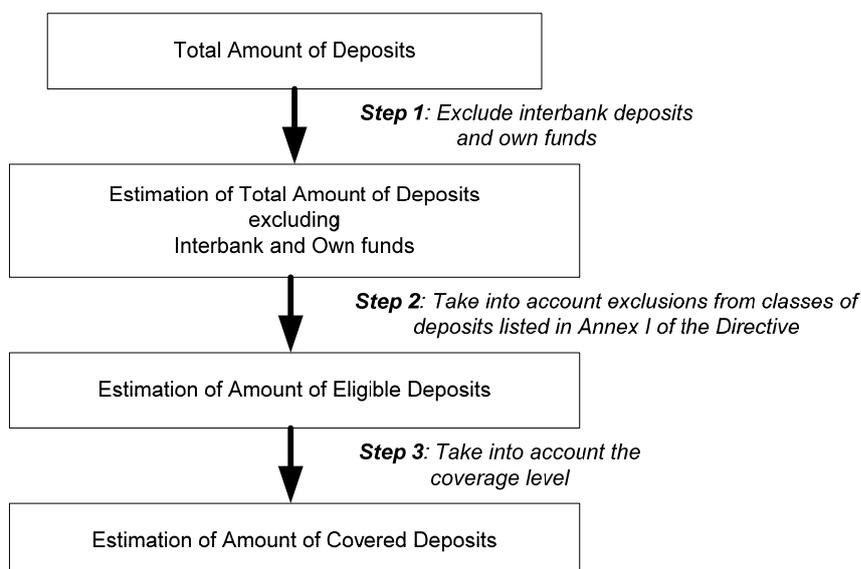


Figure 6: Methodology to estimate the contribution base for a given bank.

Despite the fact that Bankscope™ includes data for over 5 000 European banks, the level of details available can vary from one bank to another. The sample of 826 banks listed in Table 6 represents the largest set of banks for which values for all the 8 financial indicators proposed for the first two models were available (see Table 2). The reference year for data collection is 2007, as a significant number of banks had not published their 2008 financial statements at the time this report was produced.

## 4.2 Results

The purpose of the numerical experiments that will be described below is to provide a quantitative assessment of the impact the introduction of both the Single Indicator Model and the Multiple Indicators Model would have on DGS members' contributions, highlighting their differences, advantages and weaknesses.

To give an indication of the impact the introduction of each model would have, contributions under the Single Indicator Model and the Multiple Indicators Model are compared with those estimated under the funding mechanism currently adopted by each DGS. In particular, the relative percentage change in contribution is calculated:

$$\Delta = \frac{\text{Estimated Current Contribution} - \text{Single or Multiple Indicator Contribution}}{\text{Estimated Current Contribution}} \quad (5)$$

### 4.2.1 Results for the Single Indicator Model

#### Assumptions

To obtain contributions under the Single Indicator Model, we need to set the values of coefficients  $\alpha$  and  $\beta_i$  (see Section 3.1). The value of the first coefficient is the same for all banks and depends for instance upon specific conditions in the banking market or is related to the target fund of the DGS; the second describes the risk behaviour of each bank. Two main assumptions are made to set the values of these coefficients:

- 1) The overall contribution under the Single Indicator Model (i.e. the sum of the contributions paid by all the banks covered in the sample) equals the estimated overall contribution made under the current funding systems. In other words, the coefficient  $\alpha$  in the first model is chosen so that the aggregated amount of current and risk-based contributions are the same. This assumption is made in order to compare the two sets of contributions.
- 2) The values for the  $\beta_i$  coefficient are set within the range of 80% (for the least risky banks) and 150% (for the most risky banks). The penalty on 'risky banks' is in relative terms higher than the reward obtained by 'safe banks'. Table 7 presents, for each of the 8 financial ratios, the values of  $\beta_i$  depending on the quantiles of the ratios' distributions.

**Table 7: Single Indicator Model: values of the coefficient  $\beta_i$  as a function of the quantiles of the distribution of each financial ratio.**

Financial indicator	Quantile 0 to 10	Quantile 10 to 20	Quantile 20 to 25	Quantile 25 to 40	Quantile 40 to 60	Quantile 60 to 80	Quantile 80 to 100
CA1	150%	125%	125%	100%	90%	80%	80%
CA2	150%	125%	125%	100%	90%	80%	80%
AQ1	80%	80%	90%	90%	100%	125%	150%
AQ2	80%	80%	90%	90%	100%	125%	150%
P1	80%	80%	90%	90%	100%	125%	150%
P2	150%	150%	125%	125%	100%	90%	80%
L1	150%	150%	125%	125%	100%	90%	80%
L2	80%	80%	90%	90%	100%	125%	150%

### Analysis of results

For each MS and each bank, the percentage change in contribution (see Equation (5) above) is estimated using each of the 8 indicators.

To analyse the impact on banks within a given country, we will use the example of Denmark, and present in Figure 7 what would be the range of variation of the percentage change in banks' contributions, across all the indicators. The impact is measured as the maximum (percentage) increase/decrease in contributions compared to what would be paid under the current contribution systems.

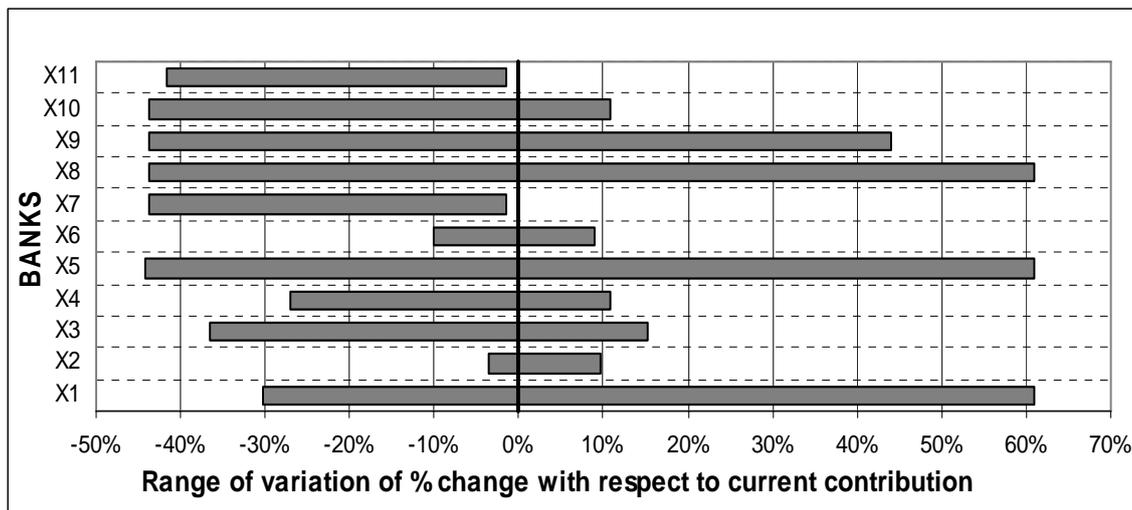


Figure 7: Denmark — Range of variation of the percentage change in contributions for the Single Indicator Model. The range depends on the choice of the risk indicator.

A couple of observations are worth highlighting from this figure:

- 1) With the exception of two banks (X7 and X11), the implementation of the Single Indicator Model sometimes results in an increase of the contribution and sometimes in a decrease, depending on which of the 8 indicators is chosen. For example, for Bank X6, the contributions would increase by up to 9% or decrease by 10% depending on the indicator chosen.
- 2) As illustrated by the spread between the maximum increase and the maximum decrease, the variability of results for most of the banks is significant. Therefore a change in the indicator selected could have a significant impact on the level of contribution paid by individual banks. For instance, in the case of Bank X8, depending on the indicator chosen, the maximum reduction in contributions would be 44% while the maximum increase would be 61%.

The above observations can be transposed to all the other countries covered in this analysis. Annex III presents the plots for each of them, if the sample of banks is higher than 5 credit institutions. Namely, analysis is performed for these MS: Belgium, Bulgaria, Cyprus, Spain (all the 3 schemes), Greece, Ireland, and Lithuania.

To get a general overview of the impact of choosing the Single Indicator Model, Figure 8 presents the maximum increase/decrease in the contributions for each country across all banks and across all indicators.

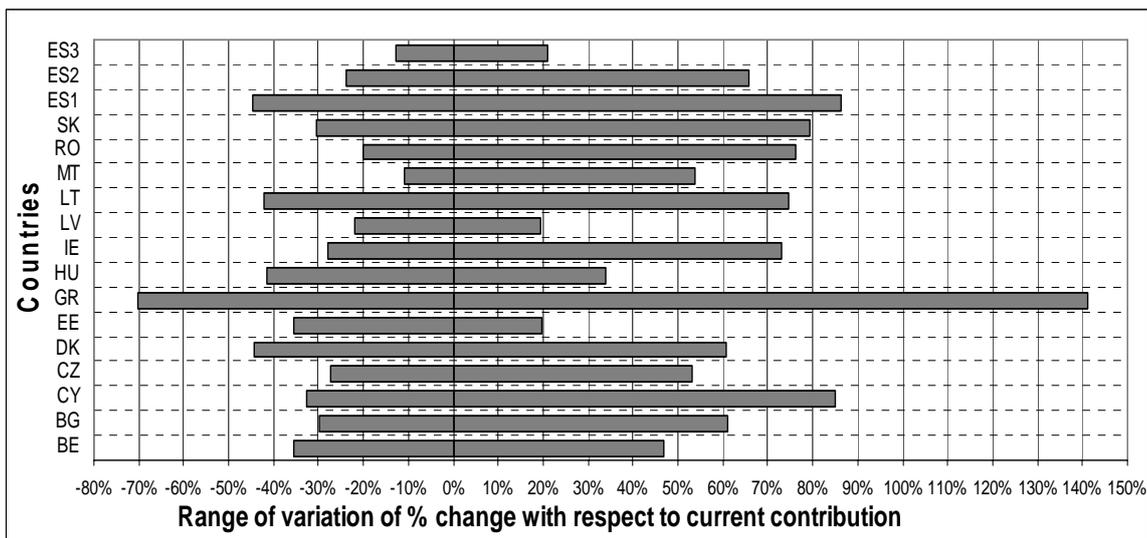


Figure 8: Single Indicator Model: maximum increase/decrease of banks' contributions (in %) relative to current contributions.

For example, the results for Belgium should be read as follows: when applying the Single Indicator Model, using any of the 8 indicators, the maximum reduction in contributions would be 35% while the maximum increase would be 47%.

Figure 8 shows the wide variability that the adoption of the Single Indicator Model would have on contributions: the average maximum increase (over the complete sample of banks) and the average maximum decrease in contributions would be +19.6% and -27.8% respectively.

A couple of country-specific comments should also be added:

- For Spain, the sample of banks was split into 3 groups to mirror the structure of DGS currently existing in Spain (ES1 for banking establishments, ES2 for credit cooperative banks, and ES3 for savings banks).
- For Greece, the wide range of variation reported for this country is the result of specificities of the Greek current funding mechanism.<sup>20</sup>

The above discussion has focused on the maximum decrease/increase resulting from adoption of the Single Indicator Model across the 8 indicators. To have an idea of how the contributions vary for a given indicator, the average and the standard deviation of the relative percentage change in banks' contributions has been calculated for each individual indicator. These results are reported in Annex IV.

To assess whether this model properly captures the risk profile of the banks we look at the correlation between the 8 financial indicators. A risk-based model where only one of the indicators is taken into account would be acceptable for consideration if there is evidence that all the indicators are highly correlated, and are therefore measuring the same underlying phenomenon.

<sup>20</sup> Under the current Greek funding mechanism different percentages are applied to different ranges of eligible deposits. Those percentages decrease very rapidly with the size of the deposits. This results in very big banks paying 'current' contributions that are not significantly higher than those paid by much smaller banks. So, if a model where contributions are proportionate to the size of the deposits is introduced (such as the Single Indicator Model), it will result in a significant increase of the contributions for the very big banks (i.e. the size effect will outweigh any risk effect). For the smaller banks, the same effect in the opposite direction will take place, given that we are assuming that the overall contribution amount does not change.

Figure 9 plots the correlation coefficient between indicators belonging to different categories ('inter-categories' correlation). In other words, we measure all possible pairwise correlations except those between indicators belonging to the same category, (i.e. between CA1 and CA2, between AQ1 and AQ2, between P1 and P2, and between L1 and L2). The correlation coefficients are intended to measure how related each pair of indicators is, using the values of those indicators for all the banks in the sample. Only countries with 10 or more banks in the sample are considered in this analysis, regardless of the type of funding mechanism adopted, i.e. FR, IT, NL, PT and UK are included.

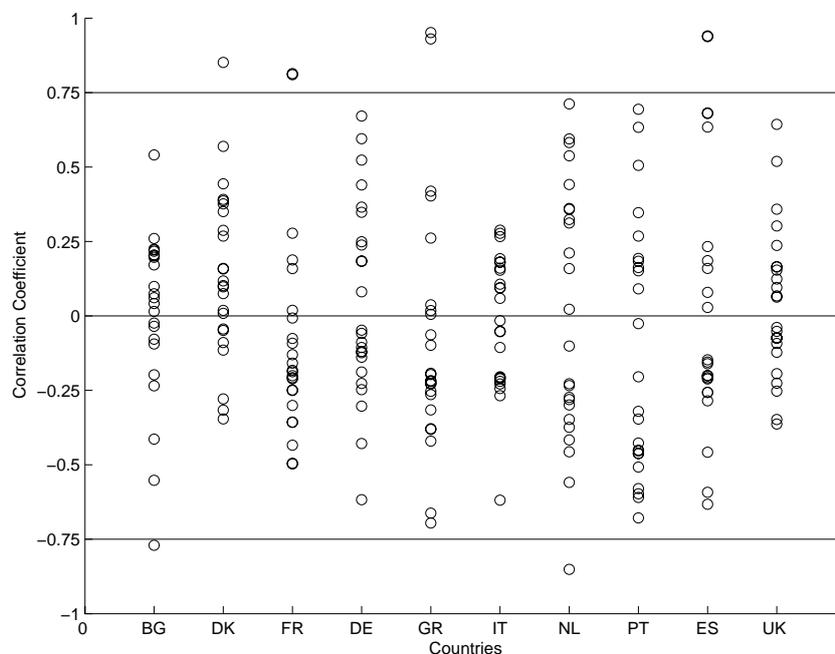


Figure 9: Pairwise correlations between indicators from different categories.

If the different indicators for a given country were all measuring the same underlying phenomenon, we would expect a significant number of correlations to be close to +1 or -1<sup>21</sup>. As illustrated by the above figure, this does not seem to be the case. Indeed, most of the correlations are distributed in the [0.75,-0.75] range. For example in the case of the UK or Greece, most of the pairwise correlations are in the range [-0.5, 0.5]. The fact that the values of the correlation between indicators of different categories are not close to +1 or -1 is an indication that by combining indicators from different categories additional information might be captured.

### Conclusions on the Single Indicator Model

Although the Single Indicator Model is simple in its approach, there is some evidence from the numerical experiments that:

- 1) the selection of only one of the 8 indicators would ignore valuable information on the risk profile of the bank that is captured by the other indicators;
- 2) the impact on contributions is very different depending on the indicator that has been selected.

<sup>21</sup> Negative correlations are a result of the fact that the 8 financial indicators considered in this exercise do not all move in the same direction. For some of them (AQ1, AQ2, P1 and L2), the higher their values are the riskier the bank should be. The others (CA1, CA2, P2 and L1) move in the opposite direction: the lower their values are, the riskier the bank should be.

## 4.2.2 Results for the Multiple Indicators Model

In contrast with the Single Indicator Model, under the Multiple Indicators Model the risk profile is set by combining multiple indicators from the 4 classes of risks described in Section 2 (i.e. capital adequacy, asset quality, profitability, and liquidity).

The following quantitative assessment results from a simulation of the contributions members would have made under the Multiple Indicators Model using 2007 as the reference year for any data needs. The simulation covers two scenarios (A and B). For each scenario, 4 indicators are considered, one for each of the 4 risk classes. Table 8 lists the indicators considered for each scenario. Simulated contributions under scenarios A and B are compared with contributions estimated applying the funding rules currently adopted by EU DGS.

Note that among all possible combinations of ratios, only two scenarios have been considered. However, since the Multiple Indicators Model averages ratios from different classes, it is expected that different combinations of ratios taken from the same classes would not significantly change results.

Table 8: Multiple Indicators Model: choice of scenarios.

RISK CLASS	Scenario A	Scenario B
Capital adequacy	Tier 1 capital ratio (CA1)	Total capital ratio (CA2)
Asset quality	NPL ratio (AQ1)	Loan loss provision (AQ2)
Profitability	Cost to income ratio (P1)	Return on average assets (P2)
Liquidity	Liquid assets to deposits ratio (L1)	Loan to deposit ratio (L2)

### Assumptions

The Multiple Indicators Model is based on the assumption that the total amount of contributions collected by the scheme needs to be decided in advance, and then apportioned among the DGS members depending on their risk profile. The risk profile of a given bank is described by a coefficient  $\beta_i$ , which in turn is calculated using the scores  $\rho_i^{(j)}$  assigned for each of the 4 risk classes. This process is summarised in Figure 10 (see Section 3.2 for additional details). Three main assumptions are made to set the total amount of contributions to be collected and the risk profile parameters:

- 1) The total amount of contributions to be collected and decided in advance (i.e. the sum of contributions paid by all the banks covered in the sample) equals the estimated overall contribution made by the same banks under the current funding system. This assumption will facilitate comparison between the two funding systems.
- 2) Equal weights are given to the 4 risk classes. In other words, the composite score for a given bank is calculated as the arithmetic average of the scores obtained for each one of the 4 risk classes.
- 3) In line with the assumption for the Single Indicator Model, the values for the  $\beta_i$  coefficient are set within the range of 80% (for the least risky banks) and 150% (for the most risky banks). The penalty on 'risky banks' is in relative terms higher than the reward obtained by 'safe banks'.

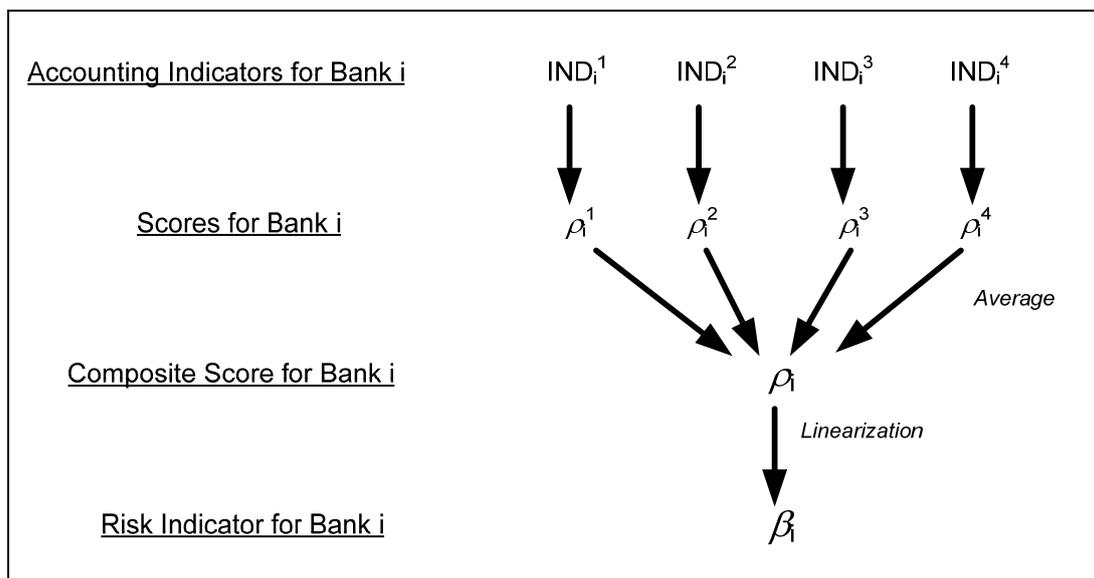


Figure 10: Multiple Indicators Model: process to compute the risk indicator  $\beta_i$  for a given bank.

### Analysis of results

To assess the impact, estimations of the contributions under the Multiple Indicators Model for the two scenarios considered (A and B) are compared with those estimated under the funding mechanism currently adopted by each DGS. The relative percentage change calculation is used for this purpose (see Equation (5) above).

The example of Denmark will be used as an illustration. Figure 11 compares the impact the Single Indicator Model and the Multiple Indicators Model would have on the individual Danish banks included in the sample. The black bar for a given bank presents the range of variation of the percentage change in contributions resulting from the implementation of the Single Indicator Model (regardless of the indicator selected). This range is the same as the one illustrated in Figure 7 (see Section 4.2.1).

The grey bar for a given bank shows the range of variation of the percentage change in contributions resulting from the implementation of scenarios A and B under the Multiple Indicators Model. For example for Bank X4, contributions would decrease by a maximum of 11% and increase by a maximum of 2%, regardless of whether scenario A or B has been chosen.

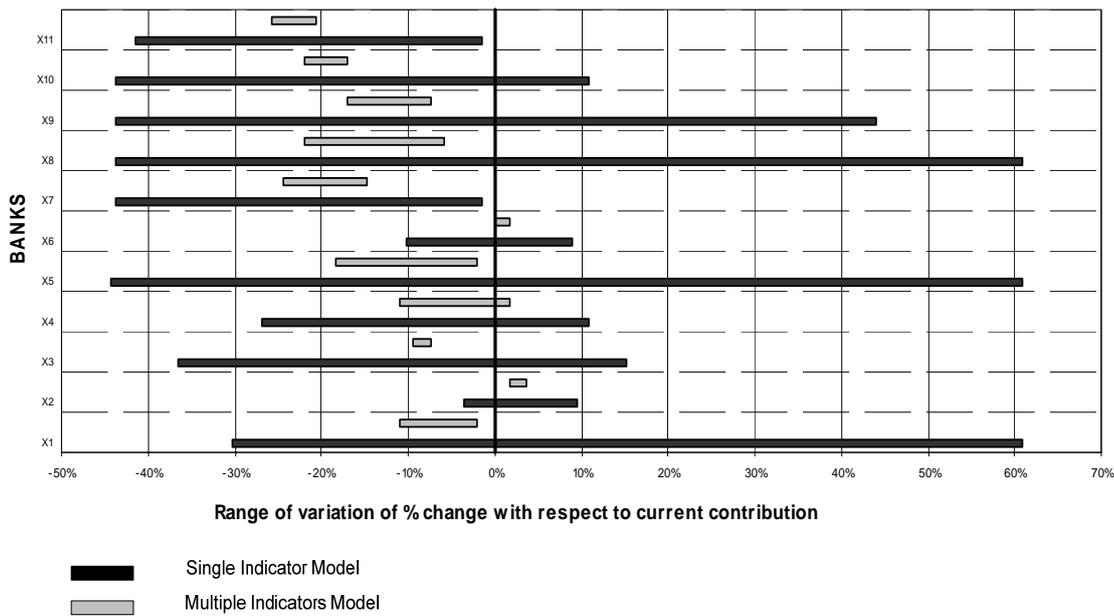


Figure 11: Single Indicator Model vs. Multiple Indicators Model for banks in Denmark: range of variation of % changes in contributions.

This figure highlights how the Multiple Indicators Model significantly reduces the variability of the changes in contributions. In other words, it is less dependent on the choice of indicators made.

The above observations can be transposed to all the other MS covered in the analysis. Annex V presents the plots for those countries having a sample of at least 5 banks.

Figure 12 aims to compare the Single Indicator Model and Multiple Indicators Model by country by looking at the range of variation of the percentage changes in contributions resulting from the introduction of these models.

The black bar for a given country covers the range of variation in contributions across all banks in the sample resulting from implementation of the Single Indicator Model. This range is the same as the one illustrated in Figure 8 (see Section 4.2.1).

The grey bar for a given country covers the range of variation of percentage changes in contributions across all banks in the sample resulting from the implementation of both scenarios A and B from the Multiple Indicators Model.

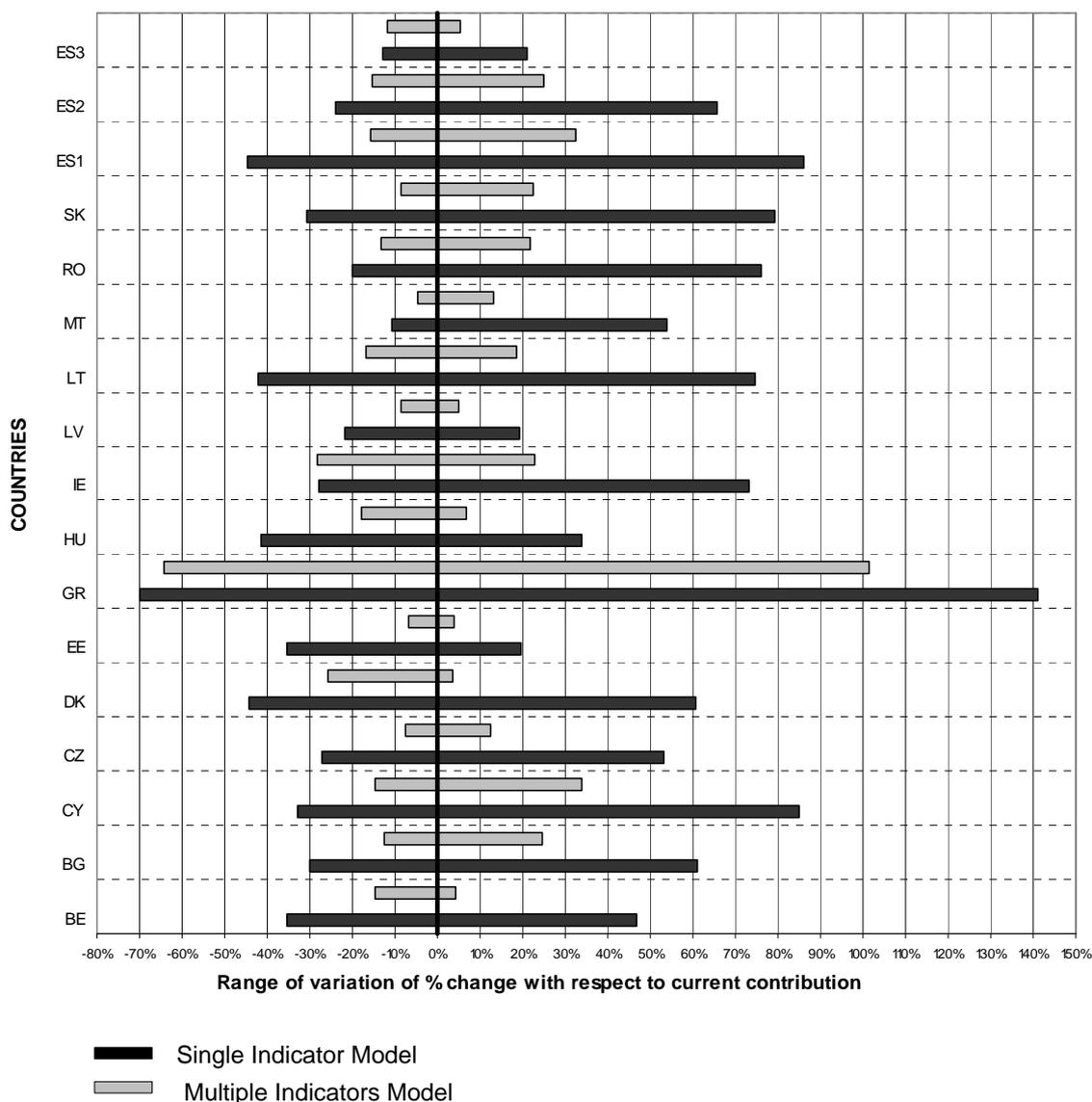


Figure 12: Single Indicator Model vs. Multiple Indicators Model for MS: range of variation of the % changes in contributions.

For example, the results for banking establishments in Spain (ES1) should be read as follows: when applying the Single Indicator Model using any of the 8 indicators, the contribution of a bank would be reduced by a maximum of 44%, or increased by a maximum of 88% (see black bar). When applying the Multiple Indicators Model (either scenario A or B), the contribution of a bank would be reduced by a maximum of 15%, or increased by a maximum of 32% (see grey bar). For an explanation on Greece, please refer to the explanations provided in Section 4.2.1 (see footnote 20).

This figure illustrates how the Multiple Indicators Model significantly reduces the variability of the changes in contributions (regardless of whether scenario A or B is used). By aggregating the whole sample, the average maximum increase/decrease would be +4.1% and -3.8% respectively.

To have an idea of how the contributions vary for a specific scenario, the average and the standard deviation of the relative percentage change in banks' contributions have been calculated for the two scenarios considered (A and B). These results are reported in Annex VI.

### Conclusion on the Multiple Indicators Model

Although it is more complex than the Single Indicator Model, the Multiple Indicators Model overcomes its main drawbacks:

- 1) Risk in a DGS context could originate from various sources (e.g. risk resulting from not having enough capital to cover unexpected losses, or risk resulting from having only illiquid assets). When moving towards a risk-based contribution mechanism, it is of crucial importance to ensure that the indicator(s) selected provide a picture of the risk that is as complete as possible. By considering indicators from different risk classes, the risk coefficient resulting from the Multiple Indicators Model is better at capturing a bank's overall risk.
- 2) There is also evidence from the numerical experiments that the variability of the impact on contributions is significantly reduced.

## 5. Conclusions

The present report describes three possible models for the introduction of risk-based contributions to deposit guarantee schemes, and presents numerical experiments for the first two to assess the impact the introduction of risk-based contributions would have on DGS members.

The first two models rely on the use of financial ratios to assess the risk of credit institutions. In line with the commonly used approaches to evaluate the financial soundness of a bank, 4 different classes of ratios covering different types of risk have been identified, namely capital adequacy, asset quality, profitability, and liquidity. For each class, two indicators were considered.

The first approach, named the 'Single Indicator Model', makes use of a single accounting ratio to categorise banks into rating classes and accordingly calculate banks' contributions. In contrast, the second approach, called the 'Multiple Indicators Model', combines 4 ratios (one per class) to obtain a single measure of the risk behaviour of DGS members. The foundations of both models rest on practices implemented by EU DGS currently adopting a risk-based contribution system. Key elements from different systems in force were combined in order to build models adaptable to different banking systems across the EU. The third model, termed the 'Default Risk Model', is based on the option pricing theory and calculates the contribution of a bank taking into account its estimated probability of default. The closer a bank is to a default situation, the more it will have to contribute.

The report presents numerical experiments aimed at assessing the impact of introducing the first two models on members' contributions. The third approach was not numerically explored since it makes use not only of accounting data but also of market price data, which is not available for many of the DGS members across the EU (as a result of not being listed on a stock exchange).

The experiment was performed on sample of banks built for this purpose using the Bankscope™ database, covering 826 EU credit institutions. In relation to the dataset, results should be read with extreme caution due to the fact that the sample of banks does not cover the entire banking market in any MS, being particularly small in some countries. However, since most of the DGS currently do not collect any data on the financial ratios of their members, or this information is not public, the use of this sample is at present the only way to assess the impact of the potential introduction of the model proposed.

Focusing on those MS currently adopting an ex-ante, non-risk-based system, estimated contributions currently paid by DGS members were compared with calculated contributions required under the two model proposals.

Results for the Single Indicator Model show that the selection of a single ratio would ignore valuable information on the risk profile of the bank, since the impact on contributions is very different depending on the indicator selected. For instance, the average maximum decrease and the average maximum increase in contributions (over the complete sample of banks) would be -19.6% and +27.8% respectively. Correlation analysis confirmed that indicators of different classes might be poorly correlated, thus weakening any potential robust conclusion.

The experiment demonstrated that the Multiple Indicators Model overcomes the main drawbacks of the Single Indicator Model. First, by considering information from different classes, the aggregated risk coefficient is better at capturing a

bank's overall risk; secondly, numerical experiments show that the variability of the impact on contributions is significantly reduced: the average maximum decrease and the average maximum increase in contributions are reduced to -4.1% and +3.8% respectively.

It has to be highlighted that the numerical experiment relies on a number of assumptions and choices being made when assigning values to the model parameters. Results should thus be carefully interpreted. The assumptions and choices made mainly covered three aspects: (i) how risk ratings are assigned to banks (i.e. choice of the quantiles of the distribution of the accounting ratios); (ii) how differences in risk profiles should be reflected in terms of contributions (i.e. choice of the corrections/adjustments); (iii) for the Multiple Indicators Model, what are the weights assigned to different indicators. All these choices can obviously be changed and adjusted by DGS to tailor the approach to their specific needs/banking system.

Future work on these proposals might focus on investigating how results would change by varying some of these assumptions (i.e. uncertainty and sensitivity analysis). In addition, enlarging the set of indicators/risk classes considered in the Multiple Indicators Model could be envisaged since results show that, for instance, indicators within the same risk classes are not always highly correlated.

Ideally, the analysis would be much more robust if some pilot DGS provided the entire dataset needed to compare current contributions with risk-based ones.

A more general issue which might be further investigated is the pro-cyclicality effect: although the use of quantiles partially mitigates this effect, the extent of the mitigation cannot be measured and strongly depends on the specific characteristics of the set of banks considered. There could be banks suffering more than others from periods of financial distress due, for instance, to the peculiar characteristics of their business. A counter-cyclical approach could be also envisaged. One possible way is to lower the total amount of DGS contribution in recession and to increase it in upturn. This line of research would be linked to the question of what should be the target size of a DGS fund.

## Annex I: Overview of funding mechanisms adopted by EU MS

Table 9: funding mechanism description, data as of 31/12/2007

MS	Base	Contribution												
BE	Eligible	0.0175% of the contribution base												
BG	Eligible	0.5% of the contribution base												
CZ	Eligible	0.1% of the contribution base for banks and 0.05% for building saving banks												
DK	Covered	Only in case the fund is below the minimum level: in case, apportioned among members on the basis of their contribution base												
DE	n.a.	n.a.												
EE	Eligible	Quarterly contributions, each 0.09% in 2007												
IE	close to eligible	0.2% of the contribution base												
GR	Eligible	A decreasing percentage is applied to different ranges: <table border="1" style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th style="text-align: left;"><u>Deposit ranges (EUR million)</u></th> <th style="text-align: left;"><u>Contribution rate</u></th> </tr> </thead> <tbody> <tr> <td>0 – 600</td> <td>0.625%</td> </tr> <tr> <td>600.01 – 2,990</td> <td>0.6%</td> </tr> <tr> <td>2,990.01 – 8,843</td> <td>0.5875%</td> </tr> <tr> <td>8,843.01 – 20,940</td> <td>0.1025%</td> </tr> <tr> <td>over 20,940,01</td> <td>0.0125%</td> </tr> </tbody> </table>	<u>Deposit ranges (EUR million)</u>	<u>Contribution rate</u>	0 – 600	0.625%	600.01 – 2,990	0.6%	2,990.01 – 8,843	0.5875%	8,843.01 – 20,940	0.1025%	over 20,940,01	0.0125%
<u>Deposit ranges (EUR million)</u>	<u>Contribution rate</u>													
0 – 600	0.625%													
600.01 – 2,990	0.6%													
2,990.01 – 8,843	0.5875%													
8,843.01 – 20,940	0.1025%													
over 20,940,01	0.0125%													
ES	Eligible	0.06% of the contribution base for banking establishments (ES1) 0.04% of the contribution base for credit cooperative banks (ES2) 0.08% of the contribution base for savings banks (ES3)												
FR	Eligible	Risk-based												
IT	Covered	ex-post												
CY	Eligible	Confidential information. The maximum amount of contribution can not exceed 0.3% of the contribution base												
LV	Eligible	Quarterly contributions, each 0.05% of the contribution base												
LT	Eligible	0.45% of the contribution base (commercial banks and branches of foreign banks) and 0.2% of the contribution base (credit unions)												
LU	Eligible	ex-post												
HU	Eligible	Quarterly contribution. A decreasing percentage is applied to different ranges: <table border="1" style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th style="text-align: left;"><u>Deposit ranges (HUF million)</u></th> <th style="text-align: left;"><u>Contribution rate</u></th> </tr> </thead> <tbody> <tr> <td>0 – 1</td> <td>0.05%</td> </tr> <tr> <td>1 – 6</td> <td>0.03%</td> </tr> <tr> <td>Over 6</td> <td>0.005%</td> </tr> </tbody> </table>	<u>Deposit ranges (HUF million)</u>	<u>Contribution rate</u>	0 – 1	0.05%	1 – 6	0.03%	Over 6	0.005%				
<u>Deposit ranges (HUF million)</u>	<u>Contribution rate</u>													
0 – 1	0.05%													
1 – 6	0.03%													
Over 6	0.005%													
MT	Eligible	From 2007, members must maintain 0.1% of their contribution base in the fund												
NL	other	ex-post												
AT	Covered	ex-post												
PL	other	Risk based												
PT	Eligible	Risk based. Contribution is calculated as a percentage of the contribution base. This amount is then adjusted using a solvency indicator												
RO	Eligible	Combination of ex-ante and ex-post. Ex-ante part: 0.1% of the contribution base												
SI	Covered	Ex-post												
SK	Eligible	Between 0.1% - 0.75% of the contribution base												
FI	Covered	Risk based. 0.05% of the contribution base + (0.125% *risk factor) of the contribution base												
SE	Covered	Risk based. Contribution = 0.1% of the contribution base, adjusted by taking into account the capital adequacy ratio												
UK	other	ex-post												

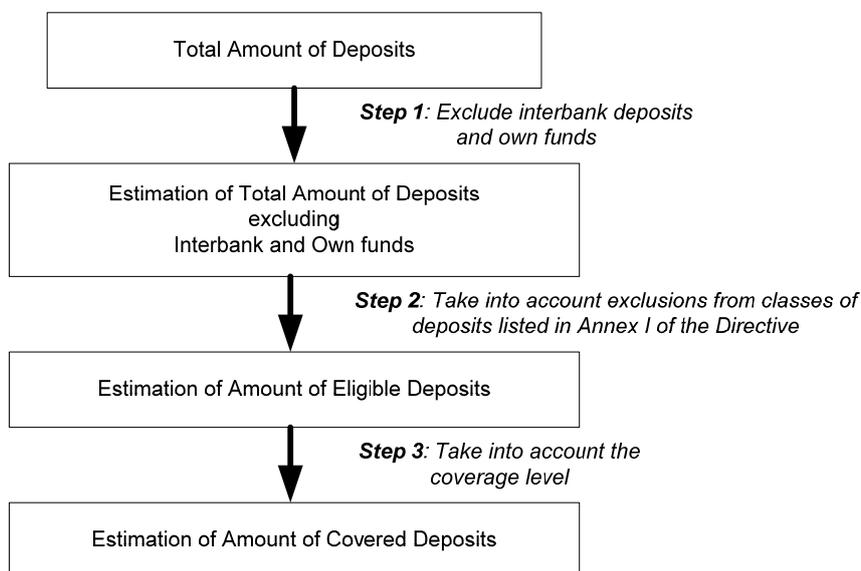
For the purpose of the numerical exercise the following assumptions were made:

- IE: We considered that the contribution base equals the eligible amount;
- LT: A contribution ratio of 0.45% of the contribution base was used for all the banks in the sample;

- CY: A ratio of 0.3% of the contribution base was used;
- MT: Contribution for all the banks in the sample equals 0.1% of their contribution base;
- SK: A contribution ratio of 0.35% of the contribution base was used for all the banks in the sample.

## Annex II: Procedure to estimate total amount of eligible and covered deposits

This annex describes the methodology to estimate the contribution base for a given bank. Depending on the country, the contribution base will either be the amount of eligible or covered deposits. The estimation process is summarized in the flow below.



**INITIAL DATA SET:** The data on deposits amount available at individual banks level in Bankscope™ is our starting point for the estimation process. We first define the “Total amount of deposits” as the sum of the following categories of deposits available in Bankscope™:

- Customer Deposits;
- Municipalities/Government deposits;
- Other Deposits;
- Commercial Deposits;
- Bank Deposits;
- Certificates of Deposit.

It should be noted that in the definition that Bankscope™ uses for “Total Deposits”, the category “Certificates of Deposit” is not included. However, in the DGS context and taking into account how “deposits” are defined in the Directive EC/94/19, it was decided to include them. The amounts reported under this category are not significant though.

### STEP 1 – Estimation of the Total Amount of Deposits excluding Interbank and Own Funds

Article 2 of the Directive EC/94/19 excludes from any repayment by guarantee schemes “interbank deposits” and “own funds”. To take this into account, we subtract from the “Total Amount of Deposits” the following categories:

- Bank Deposits: Interbank deposits;
- Other Deposits: By definition these do not represent deposits from customers, and should therefore include banks' own funds.

## STEP 2 – Estimation of the Amount of Eligible Deposits

Article 7 (2) of the Directive gives the possibility to Member States to exclude from protection certain type of deposits or depositors (as detailed in Annex I of the Directive). The amount calculated in Step 1 needs therefore to be adjusted to take into account the eligibility rules adopted by each individual MS.

The layers of breakdown on deposits amounts available at bank level from Bankscope™ is unfortunately not sufficient to make those adjustments using data from individual banks. As an alternative, we estimate for each country a ratio representing the proportion of "Eligible Deposits" out of the "Total amount of deposits excluding Interbank and own funds" (herein identified as the "eligible ratio"). This "eligible ratio", specific to each country, is then applied to all the banks within a country according to this formula:

$$\text{Estimated Amount of Eligible Deposits for Bank Y from country Z} =$$

$$(\text{Total amount of deposits excluding Interbank and own funds for Bank Y}) \times (\text{Eligible Ratio for country Z})$$

To estimate the eligible ratio, we rely on the statistics on Financial Accounts (Balance Sheet Data) available from Eurostat (<http://epp.eurostat.ec.europa.eu/portal/page/portal/eurostat/home>). These statistics contain the aggregated amount of deposits held in a given country, with a breakdown by economic sector.

List of sectors:

- Non-financial corporations
- Financial corporations
  - Central bank
  - Other monetary financial institutions
  - Other financial intermediaries, except insurance corporations and pension funds
  - Financial auxiliaries
  - Insurance corporations and pension funds
- General government
  - Central government
  - State government
  - Local government
  - Social security funds
- Households
- Non-profit institutions serving households

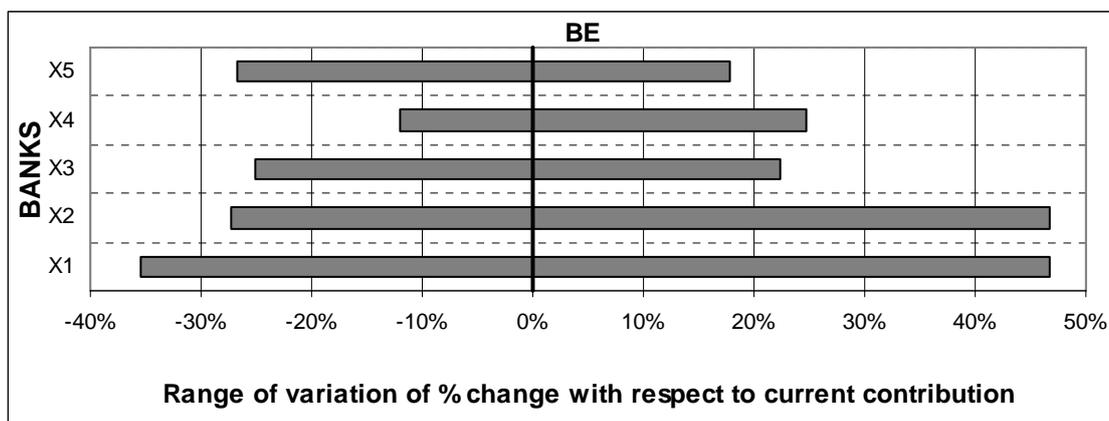
To estimate the amount of eligible deposits, the deposits from the sectors above are included or excluded depending on the specific eligibility rules applying on each country. Although with the above sectors we are not able to match all the classes of deposits listed in Annex I of the Directive, the most important ones (e.g. corporations, municipalities,...) are taken into account.

### STEP 3 – Estimation of the Amount of Covered Deposits

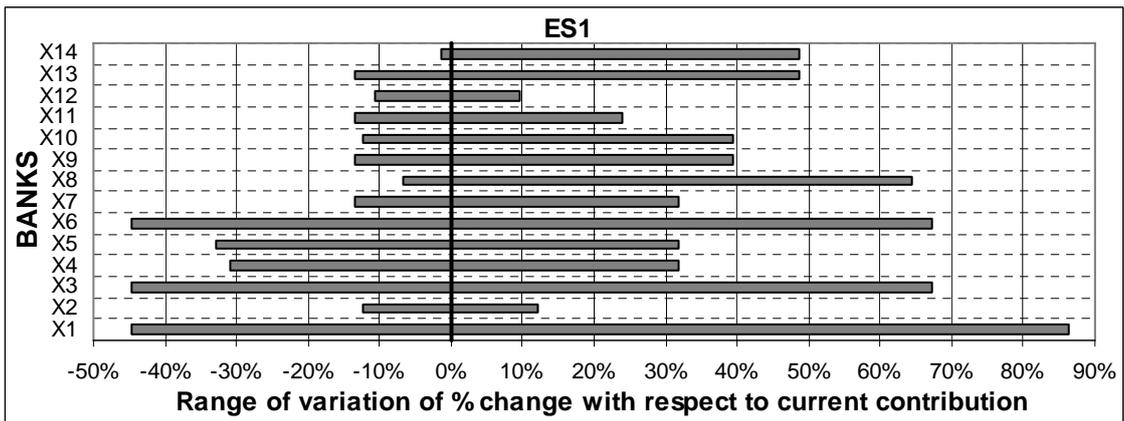
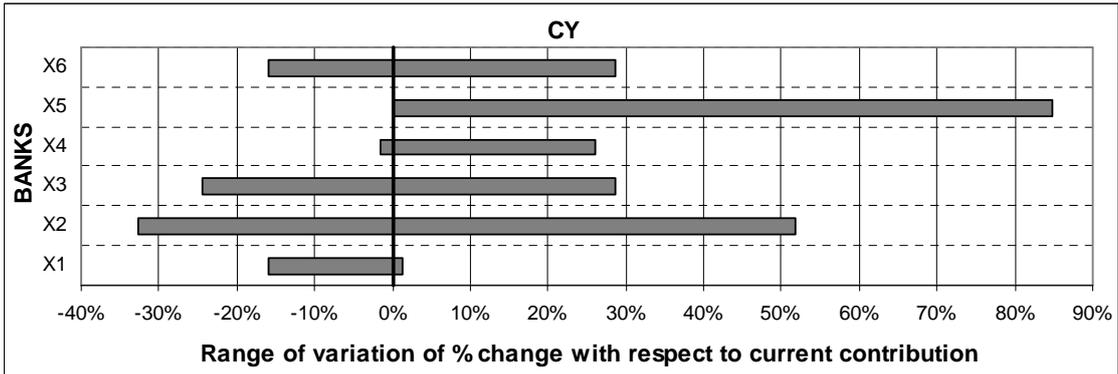
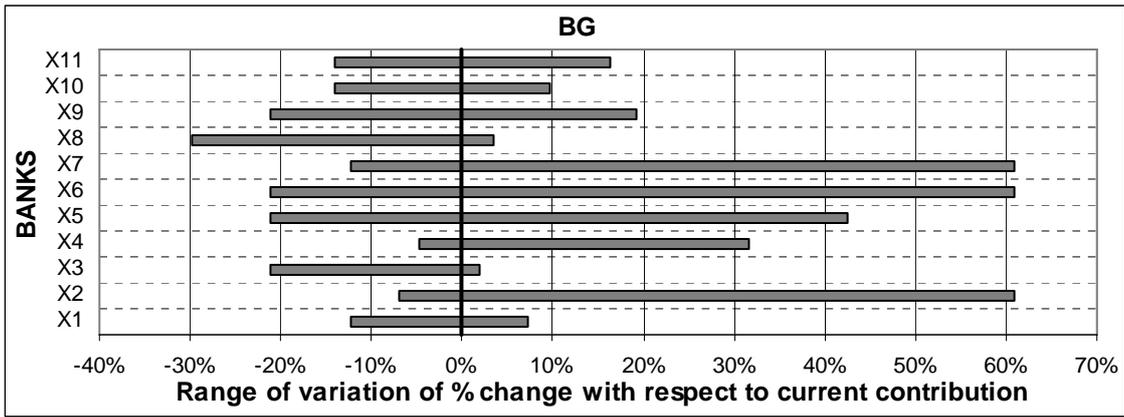
For those countries where the base of contributions is the amount of covered deposits, the amount resulting from Step 2 will be adjusted by a ratio (herein identified as the covered ratio) representing the proportion of eligible deposits that are protected. As for the “eligible ratio”, the “covered ratio” can not be calculated at the individual bank level. To estimate this ratio we use the actual numbers of eligible and covered deposits collected from DGS in a past survey<sup>22</sup>, by means of this formula:

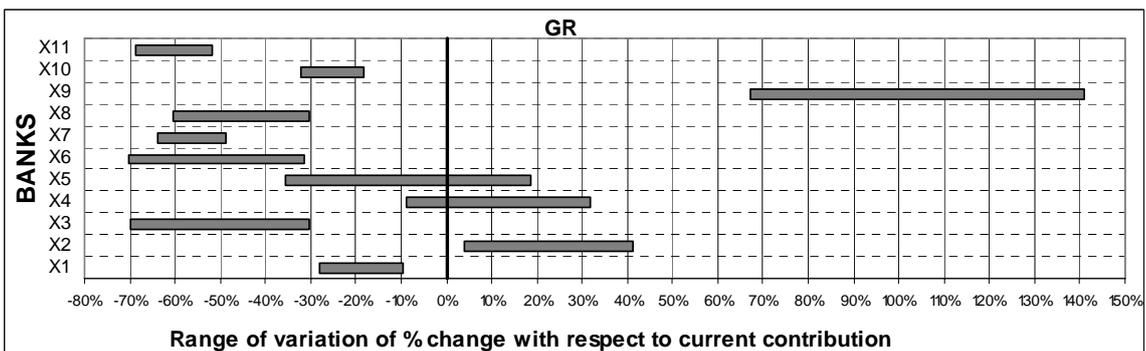
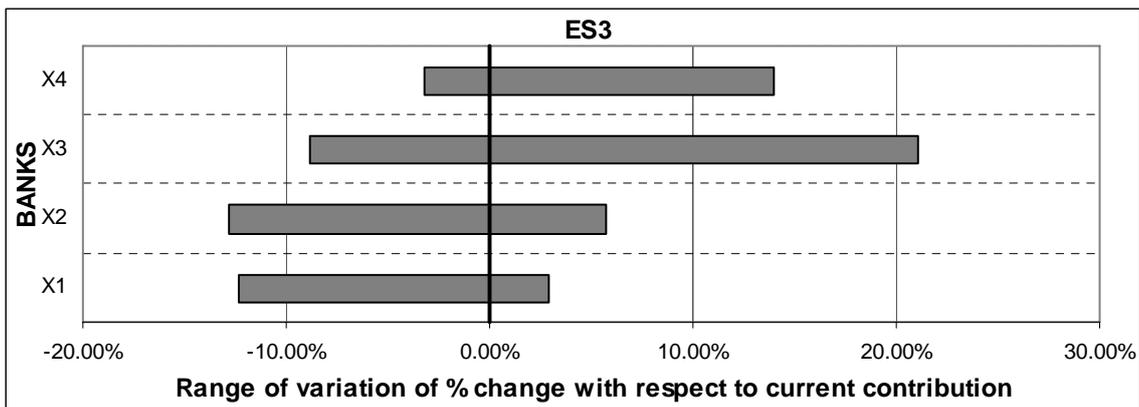
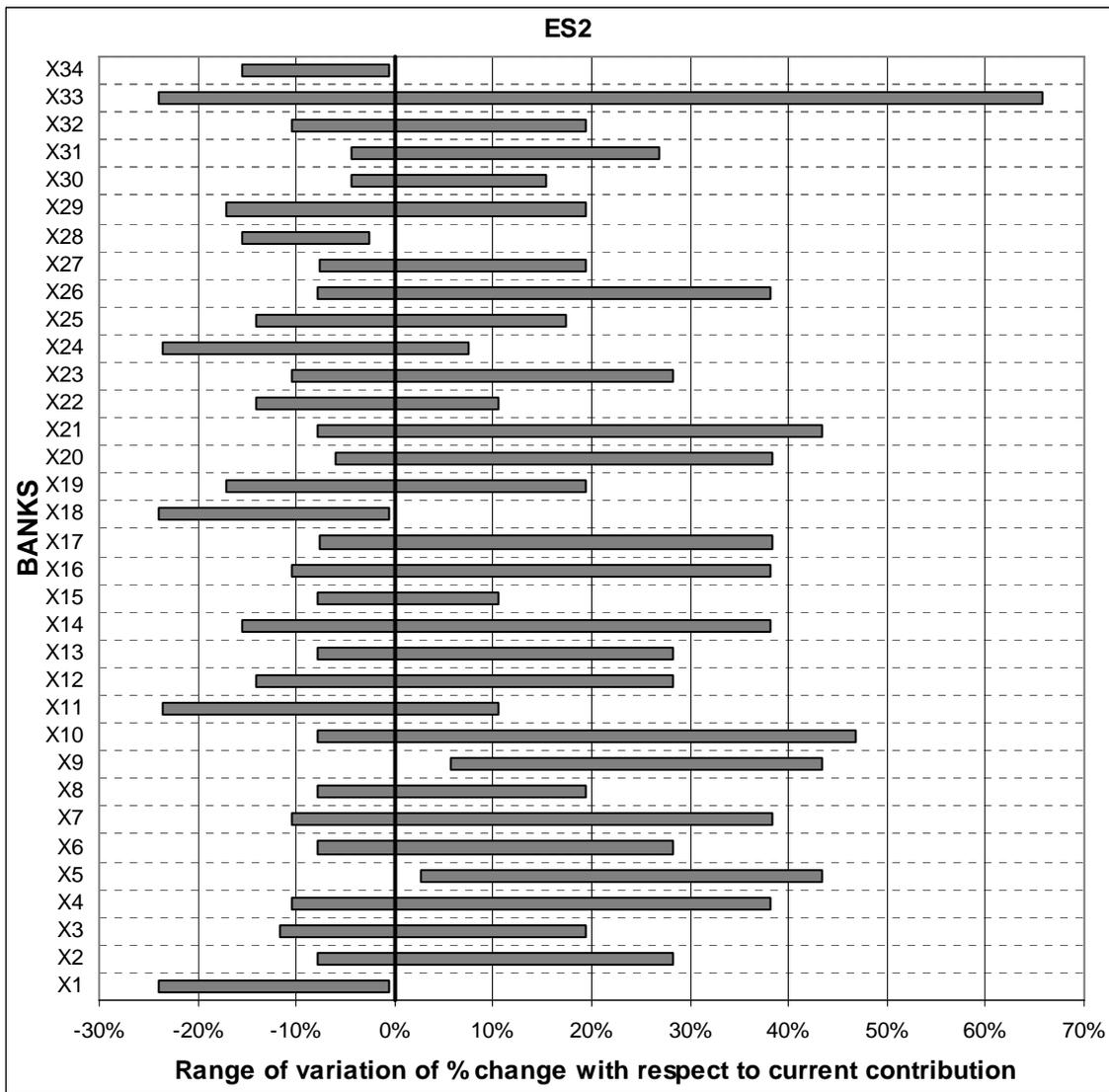
$$\begin{aligned} & \text{Estimated Amount of Covered Deposits for Bank Y (from country Z)} = \\ & (\text{Estimated Amount of Eligible Deposits for Bank Y}) \times (\text{Covered Ratio for country Z}) \end{aligned}$$

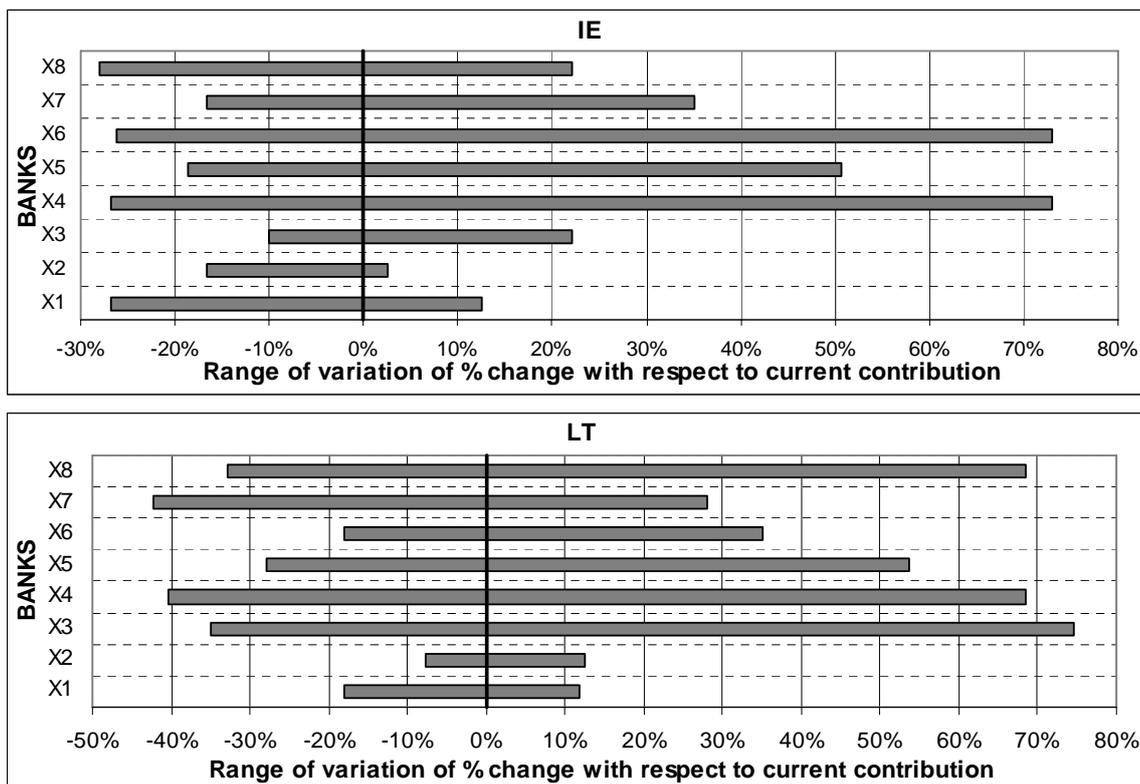
## Annex III: Single Indicator Model – Percentage of variation of banks’ contributions for each MS



<sup>22</sup> Please refer to the report “Investigating the efficiency of EU Deposit Guarantee Schemes” – European Commission, Joint Research Centre ([http://ec.europa.eu/internal\\_market/bank/docs/guarantee/deposit/report\\_en.pdf](http://ec.europa.eu/internal_market/bank/docs/guarantee/deposit/report_en.pdf))







## Annex IV: Single Indicator Model – Mean ( $\mu$ ) and standard deviation ( $\sigma$ ) of the relative percentage change in banks' contributions

Table 10: Average and standard deviation of the percentage change in contributions compared to what would be paid under the current contribution systems.

	CA1		CA2		AQ1		AQ2		P1		P2		L1		L2	
	$\mu$	$\sigma$														
BE	-9 %	17 %	-12 %	18 %	-2 %	6 %	-7 %	9 %	1 %	25 %	2 %	16 %	20 %	27 %	0 %	0 %
BG	3 %	18 %	0 %	5 %	1 %	15 %	-5 %	22 %	16 %	32 %	2 %	7 %	3 %	10 %	0 %	9 %
DK	-17 %	13 %	-26 %	17 %	2 %	6 %	0 %	16 %	18 %	30 %	-20 %	16 %	-29 %	20 %	-2 %	5 %
ES1	-12 %	18 %	10 %	23 %	9 %	23 %	-17 %	19 %	8 %	23 %	23 %	32 %	10 %	27 %	12 %	22 %
ES2	7 %	18 %	4 %	14 %	2 %	7 %	2 %	9 %	3 %	11 %	10 %	20 %	10 %	17 %	1 %	18 %
ES3	0 %	14 %	0 %	14 %	-2 %	6 %	1 %	9 %	-1 %	7 %	-1 %	13 %	-2 %	6 %	-3 %	11 %
GR	-22 %	51 %	-22 %	60 %	-18 %	47 %	-21 %	45 %	-17 %	46 %	-16 %	43 %	-17 %	49 %	-21 %	52 %
IE	-7 %	14 %	2 %	20 %	3 %	6 %	2 %	16 %	14 %	37 %	14 %	28 %	2 %	23 %	-3 %	24 %
LT	-15 %	21 %	-17 %	22 %	15 %	34 %	11 %	17 %	17 %	33 %	9 %	28 %	6 %	18 %	-8 %	22 %

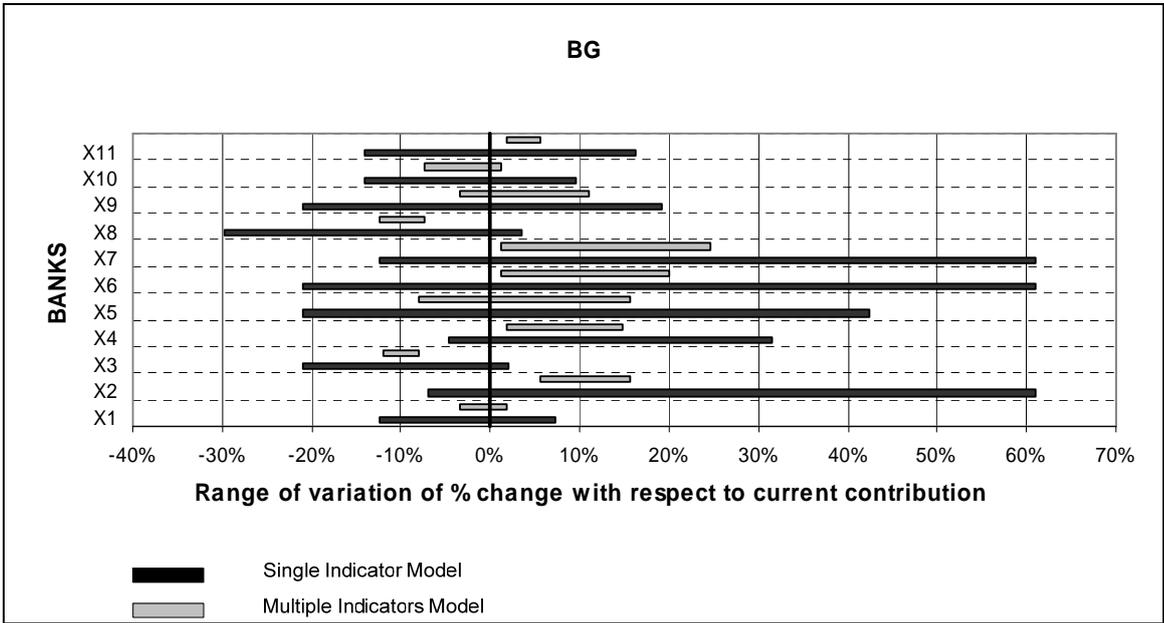
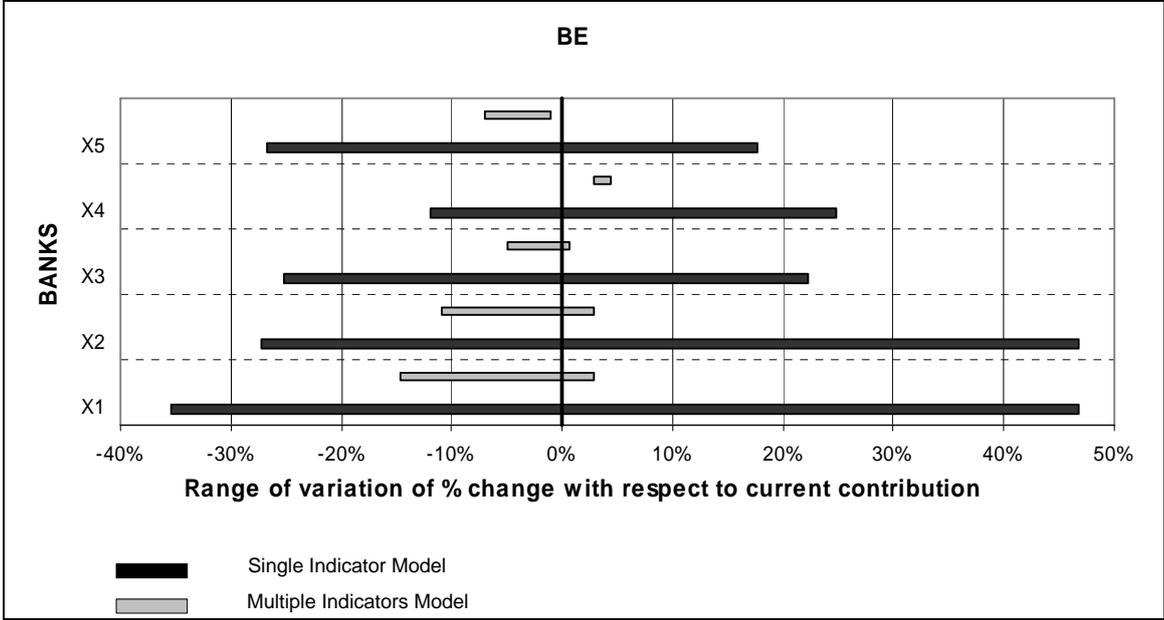
Comments: Although the numbers from the above table should be interpreted with caution given the size of the sample of banks used, what comes out of it is the significant impact the choice of the indicator has on the variation of the banks contributions. For example, in the case of ES1<sup>23</sup>, contributions would on average be reduced by 12% when the Tier 1 capital indicator (CA1) is used. However when the Return on Average Assets (P2) indicator is used, contributions would on average be increased by 23%. It should be noted that the mean in the above table is calculated as a simple arithmetic average of the percentage variation of contributions for all the banks in the sample on a given country. In other words, the size of the banks (e.g. amount of eligible deposits) is not taken into consideration in the average calculation.

Another interesting situation is the example of Belgium for the indicator L2 (Loan to deposit ratio). Both the mean and the standard deviation are 0%. This is because the value of the  $\beta_i$  risk coefficient is the same for all the banks in the sample. The introduction of a risk based contribution would in this specific scenario have no impact on the contributions paid (i.e. current contributions = risk based contributions).

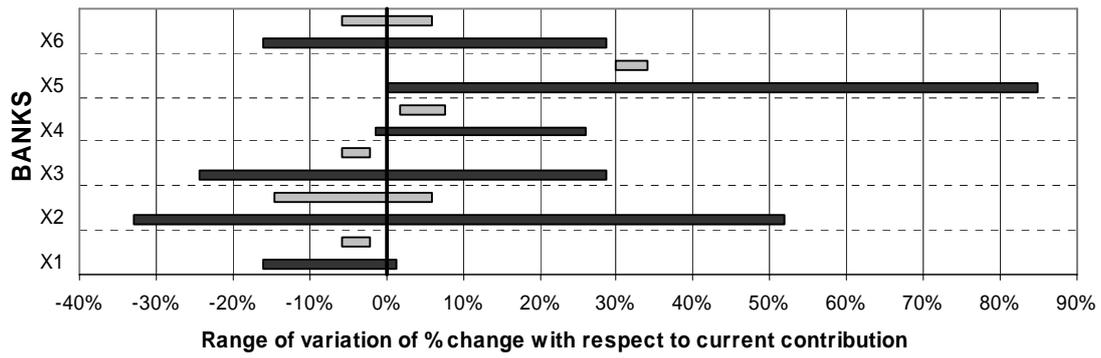
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<sup>23</sup> ES1 represents the Spanish DGS covering banking establishments.

# Annex V: Multiple Indicator Model – Percentage of variation of banks' contributions under Scenarios A and B

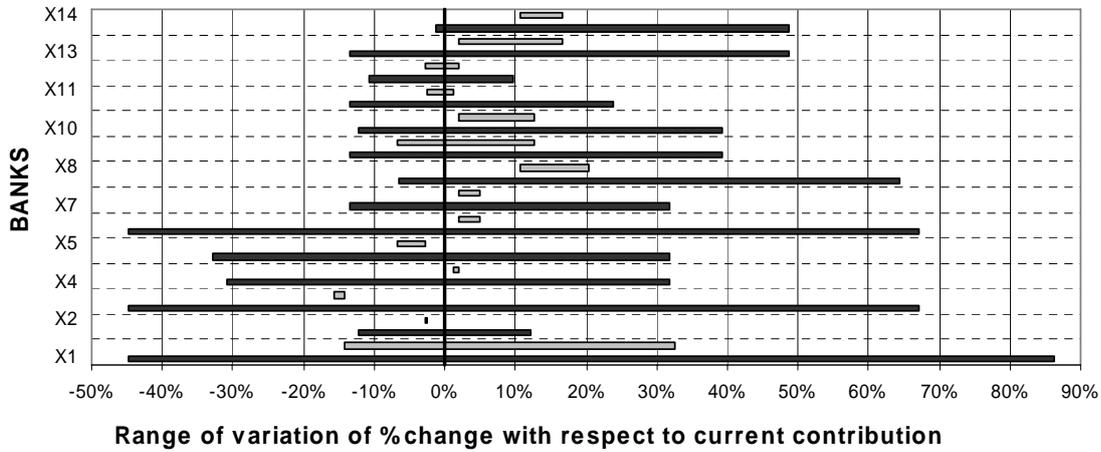


### CY

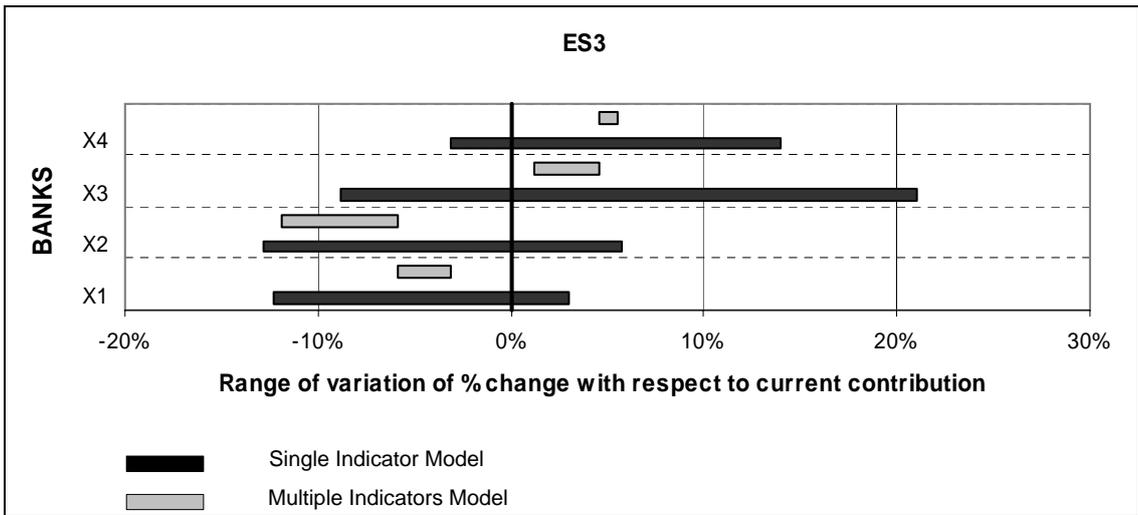
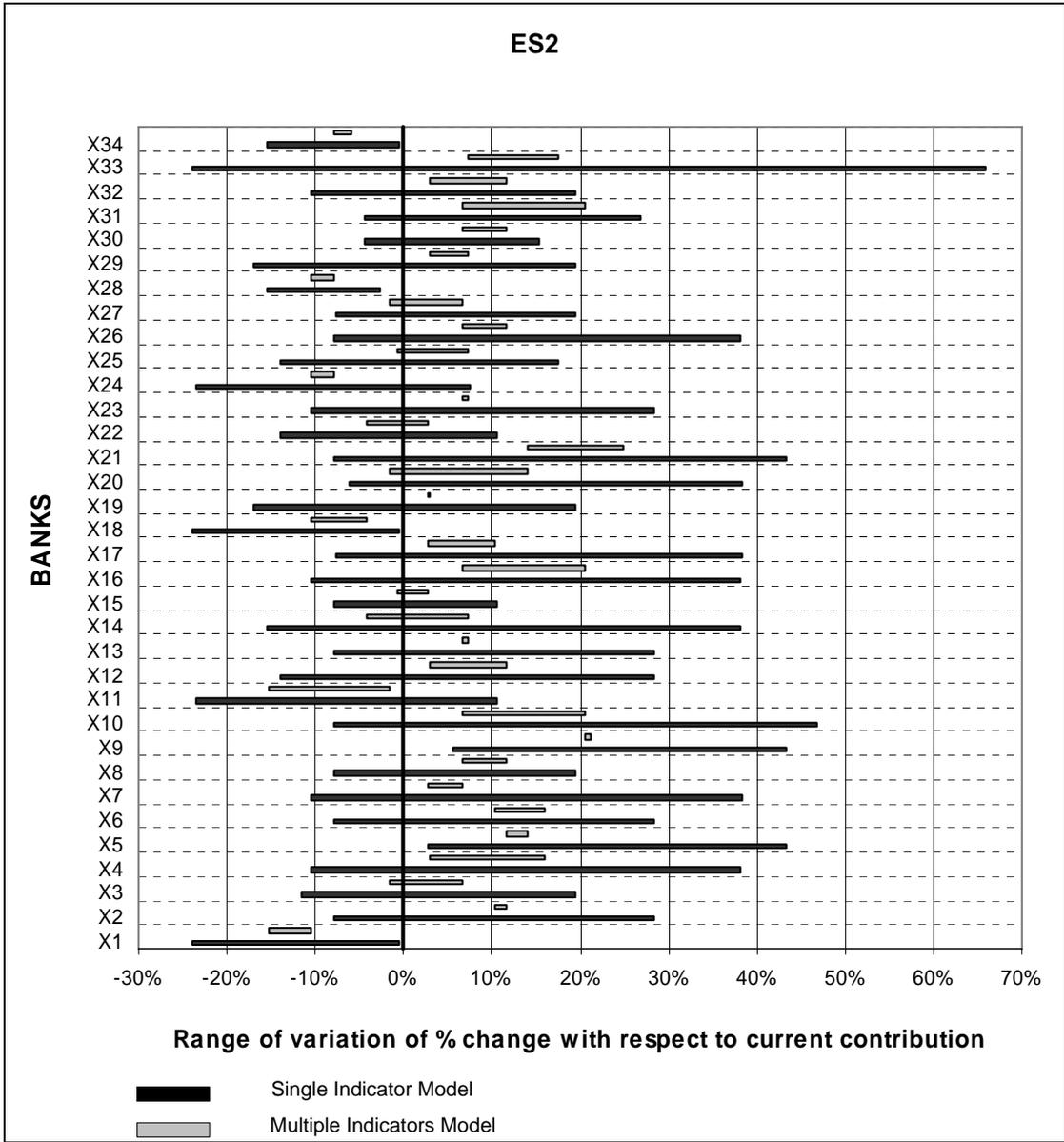


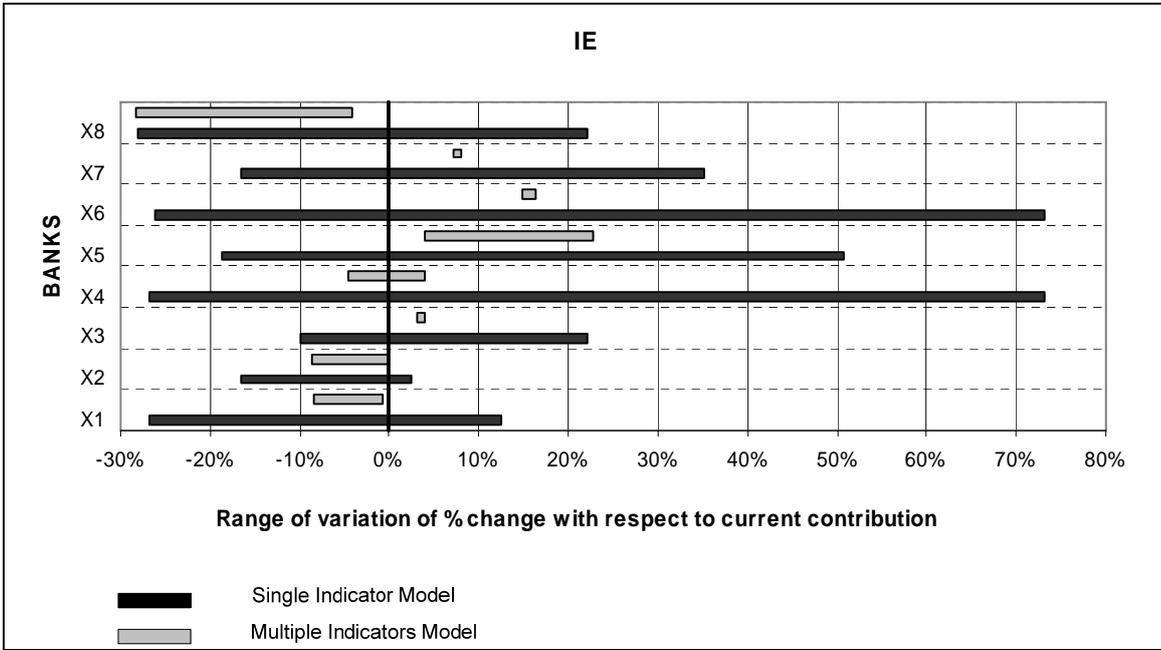
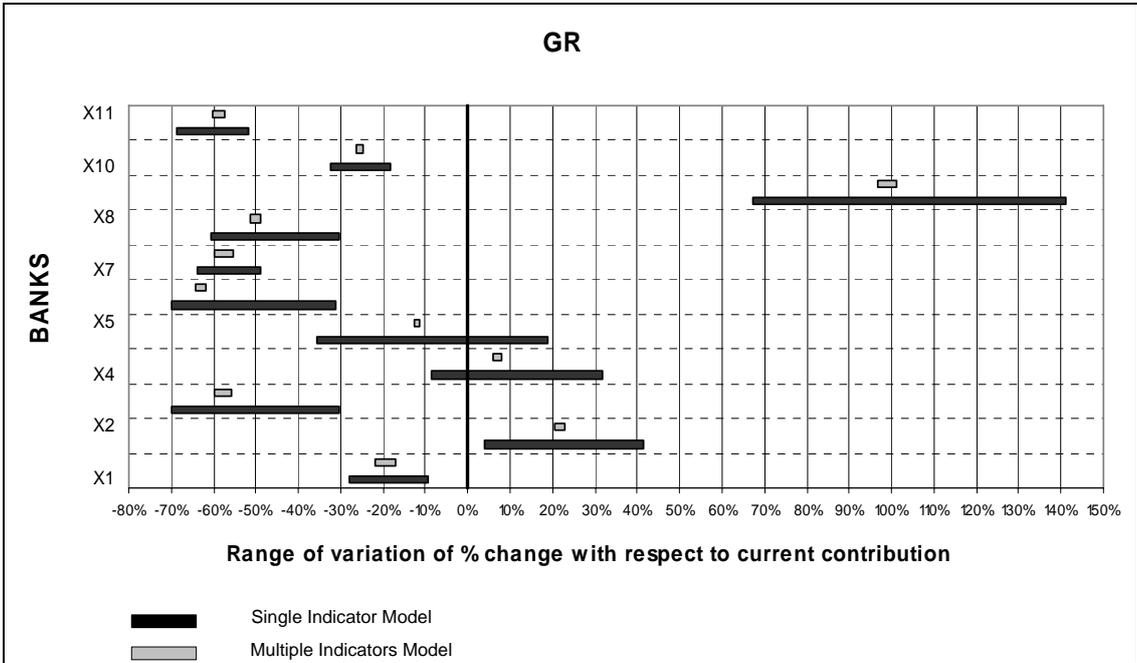
Single Indicator Model  
Multiple Indicators Model

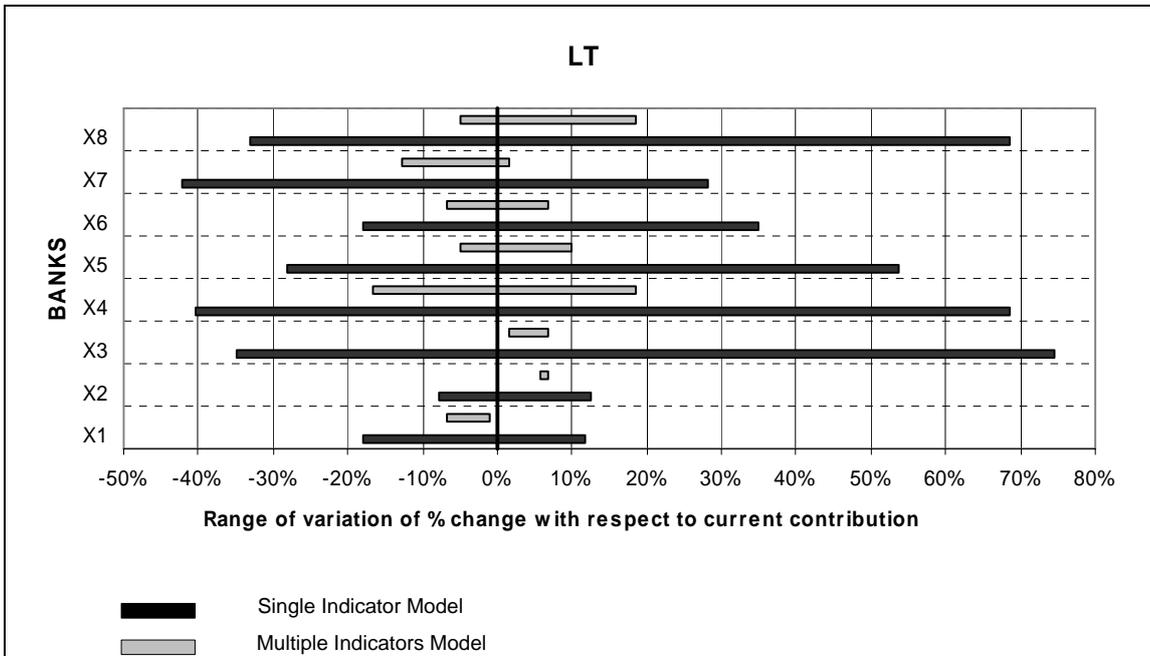
### ES1



Single Indicator Model  
Multiple Indicators Model







## Annex VI: Multiple Indicator Model – Mean ( $\mu$ ) and standard deviation ( $\sigma$ ) of the relative percentage change in contributions for Scenarios A and B

Table 11: Average and standard deviation of the percentage change in contributions compared to what would be paid under the current contribution systems.

	Scenario A		Scenario B	
	Average $\mu$	Standard deviation $\sigma$	Average $\mu$	Standard deviation $\sigma$
BE	0.48 %	3.50 %	-5.51 %	7.94 %
BG	5.98 %	12.17 %	-0.52 %	7.67 %
DK	-8.49 %	9.73 %	-12.32 %	9.31 %
ES1	2.24 %	11.06 %	3.95 %	10.93 %
ES2	6.59 %	9.73 %	3.87 %	8.51 %
ES3	-2.07 %	7.42 %	-0.64 %	5.98 %
GR	-19.26 %	48.19 %	-20.10 %	49.51 %
IE	2.96 %	7.53 %	0.72 %	15.55 %
LT	5.32 %	9.86 %	-2.41 %	9.12 %

European Commission

**EUR 24294 EN– Joint Research Centre – Institute for the Protection and Security of the Citizen**

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**Abstract**

JRC has investigated potential risk-based models for computing contributions of Deposit Guarantee Scheme (DGS) and assessed their potential impact across Member States. The report illustrates three possible approaches for calculating contributions on the basis of the risk profile of the DGS members (i.e. banks) and presents a preliminary impact assessment exercise.

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