Evaluation of Deposit Insurance Fund Sufficiency on the Basis of Risk Analysis

Discussion Paper

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Research and Guidance Committee
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I. INTRODUCTION

The International Association of Deposit Insurers ("IADI") was established in 2002 with a mission to "contribute to the enhancement of deposit insurance effectiveness by promoting guidance and international cooperation." As part of its work, IADI undertakes research and, where appropriate, suggests guidance on deposit insurance issues.

More than 80% of DI Systems in the world are ex-ante systems. And for these systems evaluation of DI Fund sufficiency is one of the most important and difficult tasks. That is why the developing of general principles and practical recommendations in this sphere is very important. These approaches could also be useful for the investment policy of the Fund since they could help to forecast the reserves needed for reimbursement payments in forthcoming periods of time. Nevertheless it should be stressed that this paper will not touch the questions of liquidity of DI Fund and it is conventionally presumed that all DIF assets are fully liquid. For simplifying reasons it is also presumed in this paper that the only purpose of spending resources of the DI Fund is paying out deposit insurance reimbursement, additional purposes for which resources of DI Fund can be spent in some countries (e.g. liquidation or financial rehabilitation of banks) are not considered in this document.

The business of deposit insurer is not a banking business, but tightly connected with it. It is also not a business of insurance company, but has some similarity with it. Deposit insurance has its own specifics and this specifics requires specific approaches to risk analysis and to evaluation of sufficiency of DI financial reserves.

In banking sphere recommendations on evaluation of banking capital sufficiency are developed in well-known Basel Principles (Basel Capital Accord) and it is very important that these recommendations are based on risk analysis.

The recommendations on evaluation of sufficiency of insurance company reserves are using a similar approach. The "Solvency 2" document (the Proposal of European Parliament and Council Directive on the Business of Insurance and Reinsurance) is based on risk analysis in a specific sphere of insurance company business.

It means that the Main Stream in recommendations on evaluation of financial reserves sufficiency exists and the general principles and practical recommendations on evaluation of DI Fund sufficiency should be developed in accordance with this Main Stream - on the basis of analysis of specific risks in the sphere of deposit insurance.

The objective of this paper is to represent the first variant of common recommendations on which approaches and which models it is better to use for evaluation of DI Fund sufficiency, which values of main parameters should be taken in the simpler or in advanced approaches.[1]

II. TERMS AND DEFINITIONS

To gain a fuller understanding of risk analysis methodologies and approaches to evaluation of DI Fund sufficiency on the basis of risk analysis, it is helpful to highlight the definitions for the following specific terms, which are used throughout the paper:

Back-testing – a method of model testing based on historical data. Back-testing is performed on control samples that do not overlap with any of the learning samples.

Dynamic balance equation – an equation that determines the volume of a DI Fund in continuous flow of time, i.e. taking into account all parameters both increasing and decreasing the volume of DI Fund at any given moment.

Expected losses (EL) - the "usual" or average losses that a DI Fund incurs under normal circumstances of Deposit Insurer's business. Mathematically EL can be defined as the mean of a DI Fund's loss distribution.

Exposure at default (EAD) - total value of insured deposits in a member bank.

Extrapolation of past dependencies – using the prior period data to define the general trend and its future extension. This assumes that all basic factors affecting the outcome will proceed in the future and a definite trend will remain.

Econometrical (Statistical) Model - a model that estimates the financial state of member banks as a statistical function of its past financial performance and other relevant parameters, so that to maximize the similarity between the observed and estimated financial standings.

Margin of safety – the exceeding of the actual value of a DI Fund over the minimal benchmark estimated on the basis of risk analysis.

Mapping procedure – a procedure of making correlation between credit ratings and probabilities of default.

Loss given default (LGD) - share of non-recoverable (non-returnable to DI Fund) resources from the bankruptcy estate of a liquidated member bank.

Regression analysis – mathematical analysis of dependency of interrelated parameters on the basis of statistical data on these parameters for the prior periods.

Reduced-form model – model that estimates financial state of a member bank on the basis of analysis of a segment of its accounting balance-sheet structure (e.g. market value of bonds, etc.) (sometimes this kind of models is called Spread Model).

Stress testing - the method of testing of a given system or entity stability in condition beyond the normal operational capacity, often in a breaking conditions, in scenarios of extreme changes in colligated risk factors.

Scenario analysis - the technique that allows one to make the variants of forecast incorporating both the observed behavior of significant indicators and the expert estimates.

[1] It should be stressed that the main approaches recommended in this paper are connected with a detailed method of analysis based on risk estimations in each DIS member bank while an aggregate method of risk analysis in DIS as a whole could also be effective.

Structural Model – model that estimates financial state of a member bank and its default process on the basis of analysis of its accounting balance-sheet structure, i.e. its financial structure (market value of equities, assets, liabilities) (sometimes this kind of models is called Distance to Default (DD) Model).

Target reserve ratio (TRR) –the ratio of DI Fund value to the total amount of insured or insurable deposits (depending on existing practice) set as a benchmark.

Value-at-Risk concept (VaR) – concept of estimation of any economic parameter value taking into account its risks.

Probability of default (PD) –probability of a bank failure on its obligations calculated as an independent variable.

Unexpected Losses (UL) - extraordinary losses of the DI Fund that can occur under unlikely, yet possible unfavorable outcomes, which, however, are not considered as systemic crisis scenarios. Mathematically UL is the deviations from the average – expected losses (EL) – with a certain level of probability i.e. on a certain level of confidence.

III. PRELIMINARY REMARKS, IMPORTANT FOR EVALUATION OF DI FUND SUFFICIENCY

Before starting description of basic approaches to estimation of deposit insurance fund (DI Fund) sufficiency there should be made two preliminary remarks which are based on recognition of the role and mandate of a deposit insurance system.

A. Systemic Crisis Limitations

DI Fund should be sufficient for serious difficulties in banking sector but *not for systemic banking crisis* [2]. Otherwise a DI Fund needs to be commensurable with the total volume of insured deposits. Accumulation of such DI Fund is hardly feasible and has no economic justification.

In systemic crisis Deposit Insurer should be supported by external sources of funding (state budget etc.). It means that DIF should have a reasonable upper limit which is determined by the definition of "systemic banking crisis".

It is necessary to stress that definition of systemic banking crisis is out of the scope of this paper and is a task for national legislators, as well as banking industry supervisors and deposit insurers.

B. Deficit Tolerance

Deficit of DI Fund should not mean termination of DIS functioning.

Since the objective of a DIS is not only to distribute the risk among member institutions, but also to distribute the risk in time, under certain conditions maintaining negative balance of DIF can be more reasonable than extraordinary financing of DI Fund from state budget, issuing of debt instruments or charging extraordinary premiums from member banks. In practice there are well known the cases of effectively execution of DIS functions in case of DIF deficit[3].

C. Dynamic Approach

Movement in deposit liability of the banking sector requires the constant review of DI Fund sufficiency at different intervals as well. In some jurisdictions, changes in deposit liability over time may be minimal while in others changes may be more noticeable. Therefore, it is important that DI Fund sufficiency should be taken in the context of a moving target.

[2] According to the Core Principles approved by IADI and presented to the Financial Stability Forum in March 2008 "A deposit insurance system can deal with a limited number of simultaneous bank failures, but the resolution of a systemic banking crisis requires that all financial safety-net participants work together effectively". See www.iadi.org

[3] Canada and Japan are well-known instances.

IV. TWO BASIC METHODS OF EVALUATION OF DI FUND SUFFICIENCY

There could be distinguished two basic methods of evaluation of DI Fund sufficiency:

- On the basis of *expert opinions* (without estimation of *PD* of member banks)
- On the basis of *risk analysis* (on the basis of estimation of *PD* of member banks).

A. Expert Opinion Method

This method is based on ideas of some respected experts about the «margin of safety» which the DIF should have.

In fact, the sufficient level (size) of the DI Fund in this case is set without evaluation of current probability of default (PD) of member banks and without taking into consideration the level of insurance liability of the DI System (in particular the value of DI coverage).

Usually a target reserve ratio (TRR) which could be called in this case an *Expert Opinion Target Reserve Ratio* lies in the centre of this method. This (Expert Opinion) TRR is calculated as the ratio of the Fund to the total amount of deposits and more often it is set by a regulation act on the basis of domestic or foreign expert ideas about DI Fund margin of safety.

It seems that such a method of setting the target reserve ratio (TRR) is far from being accurate as it estimates steadiness of a DIS without taking into consideration the level of DI potential liability which corresponds to the coverage limit. For example regardless of the coverage limit is 30 or 50 thousand dollars it does not matter for TRR according to this method. While it is evident that in case of bigger coverage limit – and consequently bigger potential liability of DI - the bigger TRR should be.

Usually this ratio does not depend on the state of banking sector and economy at all. During the periods of economic growth or during the recessions it orients the DIF at the same value. While it is also clear that in unfavorable conditions the DIF needs a bigger margin of safety.

There is one more type of reserve ratio that should be underlined separately.

In Deposit Insurance practice we can often meet a Reserve Ratio which is set not on the basis of volume of DI Fund, sufficient for reimbursement payments, but on empiric ideas about the maximum (or minimum) volume of the Fund which should never be reached.

This type of Reserve Ratio could not be called the Target Ratio because it does not represent the target of the Fund. It is more logical to call it an

Extreme RR.

As a rule the *Extreme RR* is set for determining the moments when some important parameters of DI System should be radically changed, for example DI premium rates.

Usually the value of Extreme RR is equal to high round numbers – 5% or even 10%. It is a specific feature of this type of RR. [4]

B. Risk Analysis Method

Risk analysis method of DI Fund sufficiency evaluation is based on estimation of *PD* of member banks and DI Fund cover losses. It could also assume the setting of TRR – but on the basis of risk analysis (it could be called *Risk Analysis TRR*)

This method is the main theme of this paper and all the following text is mostly devoted to it.

V. THREE CONCEPTUALLY IMPORTANT ISSUES IN EVALUATION OF DI FUND SUFFICIENCY ON THE BASIS OF RISK ANALYSIS

There are three conceptually important issues that should be carefully considered in evaluation of DI Fund sufficiency on the basis of risk analysis:

- Estimation of expected and unexpected losses of DI Fund
- Excluding "too big to fail" banks from the basis of evaluation of DI Fund sufficiency
- Orientation on the implied level of DIS financial reliability

A. Estimation of expected and unexpected losses of DI Fund

The concept of Basel II principles directs Deposit Insurers on using Value-at-Risk indicators (*VaR*) in evaluation of DIS risks.

It means that a DI Fund should be sufficient to cover (*CL* – covered losses) both expected *(EL)* and unexpected losses *(UL).*

The expected losses *(EL)* is the typical value of random value of losses under normal conditions. The unexpected losses *(UL)* is the extraordinary losses that can occur under unlikely, yet possible unfavorable outcomes, which, however, are not systemic crisis scenarios.

[4] It should be underlined that overly high rates, set by authorities could send wrong signals to DIS. The Deposit Insurer could feel obliged to set premium level at its utmost level for a longer period of time and invest DI Fund into high yield instruments in order to come closer to the TRR as soon as possible.

$$CL = EL + UL$$

The value of expected losses *(EL)* is determined by actual internal risks of member banks. Unexpected losses *(UL)* show, which deviation of losses from their expected value can be *with a certain probability*.

Thus, the value of unexpected losses *(UL)*, besides economic factors, depends also on the level of financial reliability *which is reasonably preset by a Deposit Insurer* in accordance with current conditions of economy and banking sector.

The question *how to preset this level of reliability* is one of the most important and difficult ones. Its decision is connected with the *implied level of financial reliability* (*see Section C below*).

B. Excluding "too big to fail" banks from the basis of evaluation of DI Fund sufficiency

In the majority of banking systems insured deposits are concentrated in a limited number of biggest banks. A failure of even one of such banks can exhaust the DI Fund completely. Therefore, a Deposit Insurer can reasonably expect that in case of instability in any biggest bank the Regulator will implement extraordinary measures to normalize the situation[5].

In this connection for the purposes of evaluation of DIF sufficiency there should be developed *a methodology for determining the list* of banks which are "too big to fail". These banks *should be excluded from the basis of evaluation* of DI Fund sufficiency[6].

C. Orientation on the implied level of DIS financial reliability

According to the concept of Value-at-Risk (*VaR*) a sufficient level of a DI Fund should correspond to a certain level of financial reliability of Deposit Insurer[7].

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[5] "Too big to fail" banks should be especially evaluated under systemic risk as the failure of such a bank could cause a systemic risk.

[6] It should be stressed that excluding "too big too fail" banks from the analysis of DI Fund losses does not mean excluding these banks from the DI System. These banks should remain DIS members and pay DI premiums par with all. Pretty often such banks became super large and are perceived as "too big too fail" because they are (along with the rest) the DIS members and in reimbursement payments will be supported by the State.

[7] The level of Deposit Insurer financial reliability (i.e. the level of DI Fund deficit probability) can be determined with the help of a statistic characteristic (i.e. a quantile) of the distribution of DI Fund losses in the given forthcoming period. Explanation: a q-quantile of the cumulative distribution function of a random value X is a number chosen so that the probability of X exceeding this number equals (1-q). For example:"q" is the value of a variable below which a certain percentage of statistical observations fall, e.g. a value below which, say 20 p.c. of the observations may be found.)

A *general indicator* of the level of financial reliability *is credit rating*.

It does not mean that a Deposit Insurer should receive a credit rating from any independent rating agency. It should be a simulated or so-called *"implied" credit rating of a Deposit Insurer*.

Implied credit rating can be assigned with the help of *mapping procedure* which gives the correspondence between credit ratings and the values of probability of default. For example, correspondence between credit ratings of Standard & Poor's and average historical frequency of defaults is the following[8]

Rating		**Historical frequency of default, %**	
		duration period, 1 year	duration period, 5 years
Standard & Poor's	A	0,06	0,60
	A-	0,07	0,73
	BBB+	0,15	1,74
	BBB	0,23	1,95
	BBB-	0,31	3,74
	BB+	0,52	5,41
	BB	0,81	8,38
	BB-	1,44	12,32
	B+	2,53	17,65
	B	6,27	23,84
	B-	9,06	29,44
	CCC – C	25,59	44,50

Economical logic of assigning the implied level of DIS financial reliability (i.e. of assigning the implied level of DI Fund deficit probability) is the following:

- It is deemed reasonable that the level of DIS financial reliability *should not be lower* than the *credit ratings* of the most safe and sound member banks.
- On the other hand, it is not rational *if a DIS reliability exceeds the sovereign credit rating* in particular the credit rating of national government debt obligations.

[8] http://www.standardandpoors.com/ratings/articles/en/us/?assetID=1245207201119
It should be stressed, that, empirically, average historical default frequencies corresponding to different credit ratings vary substantially with time and also with the turn of the business cycle.

- It means that the target level of DIS reliability (i.e. the target level of DI Fund deficit probability) ***should lie somewhere between these two values***.

VI. TWO INDEPENDENT TASKS IN EVALUATION OF DI FUND SUFFICIENCY

There are two independent tasks in evaluation of DI Fund sufficiency:

- *Short term* evaluation of DIF sufficiency (horizon not longer than 1 year).
- *Long term* evaluation of DIF sufficiency (horizon more than 1 year).

Main difference between these two tasks is the following. In short- term forecasting (with horizon less than 1 year), there can be applied some simplifying assumptions concerning stationarity of the system – in particular total amount of deposits in banks, income from DIF investment and some other parameters. In long-term forecasting such simplifying assumptions are not applicable, and it is necessary to use the methods of scenario analysis.

A. Short Term Evaluation

In the short term (up to a year), it is advisable to utilize an actuarial approach, under which only the actual cash flows arising over the given time horizon should be considered. The present value of the future cash flows beyond the given time horizon should not be taken into account.

Furthermore using some simplifying assumptions a deposit insurer can construct several statistic models for the DI Fund sufficient level estimation corresponding to a given solvency level of the DI System (it will be shown below).

In particular, short term analysis (up to one year) can be based on a number of assumptions concerning the stationarity of the economic environment[9] that do not result in a material loss in forecast accuracy (in analogies to assumptions about stationarity of the economic environment which are usually done in short term analysis of the credit portfolio of a commercial bank):

- Bankruptcy recoveries and investment gains are negligible (compared to DIF loss).
- Exposure is held constant over the whole planning horizon.
- Losses and inflows occur at the end of the planning horizon, thus, deficit is only possible at the end of the period.

B. Long Term Evaluation

In the long run the target level of the DIF should be set based on the notion of fair (economic) value. In accordance with the International Financial

[9] Such assumptions are inevitable for any modelling, with risk management being no exception. For instance, portfolio *VaR* measures the risks of a hypothetical portfolio under an assumption that its composition does not change over the planning horizon.

Reporting Standards[10], the fair value of the DIF should take into the account not only the market value of the deposit insurer's non-contingent assets, but also the present value of contingent assets and liabilities. The fair value of the DIF should thus be calculated as the value of non-contingent assets (cash and financial instruments) plus the expected present value of future receivables (insurance premiums and recoveries) net of the present value of future payables (insurance losses and overheads). The fair value approach to DIF sufficiency evaluation allows for temporary DIF deficits that will be covered by future receivables. The stationarity assumptions used for short-term statistical modeling of the DIF sufficiency are not acceptable for long-term planning. In particular, the possibility of credit downgrades due to deteriorating credit quality of insured banks should be taken into consideration. Long-term estimates of the DIF sufficient level should be based on scenario analysis. Essentially, a long-term estimate should amalgamate the approaches of financial planning and risk management.

In particular, alongside with statistical estimates (such as statistical models of default probability and loss given default), some inputs of the DI Fund sufficiency model (such as exposures at default or capital gains) should be based on scenario analysis, as the assumption of environment stationarity is largely untrue for longer planning horizons.

The most adequate approach to long-term DIF targeting is to use a dynamic DI Fund balance model. The dynamic balance equation of the DI Fund can be represented as:

$$\boldsymbol{B}_t = \boldsymbol{B}_{t-1} - \boldsymbol{D}_t + \boldsymbol{I}_t + \boldsymbol{P}_t + \boldsymbol{R}_t,$$

where $\boldsymbol{B}_t$ denotes Fund's balance at the end of period t,
$\boldsymbol{D}_t$ denotes the total payout to depositors over period t,
$\boldsymbol{I}_t$ denotes the investment income of the Fund over period t,
$\boldsymbol{P}_t$ denotes the insurance premiums received over period t,
$\boldsymbol{R}_t$ denotes the recoveries received over period t.

In result of dynamic balance equation modeling, the forward distribution of the Fund balance value is derived. It can be transformed into a distribution of the Fund's present value using an appropriate interest rate term structure.

Of course payout forecast is the core of the model. At the same time the significance of other elements of the dynamic balance equation varies for different planning horizons and different types of economy[11]. For example, financial market returns modeling is very important for mature economies that are typically characterized by high level of activity in the securities markets. When assessing the sufficiency of a Fund that is significantly replenished by

[10] IFRS 7 *Financial Instruments: Disclosures* – International Accounting Standards Board, 2007.
[11] The payout model is the central element of the forecast for any type of economy and any planning horizon.

investment income, one should concentrate on careful modeling the returns on investment of the DIF. For emerging markets, which are typically characterized by pronounced exponential growth of insured deposits, a crude model of investment returns can be used, but a more realistic and elaborate model of insured deposits growth is required.

It should be understood that the elements of the dynamic balance equation are not mutually independent. For instance, a systemic bond market crisis can result in simultaneous decline in investment income of the DIF and increase in losses to insured depositors of the defaulted member institutions that were most exposed to the debt market risks. Such interrelations are also generally of complex nature, meaning that the forward distribution of the DIF balance does not have a straightforward analytic expression and should be estimated using Monte Carlo simulation in an appropriate stochastic model.

Since forecasts are typically based on extrapolation of past dependencies, long-term evaluation of DIS solvency should be based on a number of realistic scenarios that take into account the possibility of future changes in the currently observed tendencies.

When evaluating the long-term adequacy of the DIF, the standard forecasting methods should be enhanced with stress-testing. The aim of stress-testing is to assess the solvency of the DIS under unlikely, yet material scenarios of extreme changes in colligated risk factors.

VII. APPROACHES TO ESTIMATIONS OF EXPECTED (EL) AND UNEXPECTED LOSSES (UL) OF DI FUND

In both kinds of analysis – short-term and long-term – the most important issue is estimation of expected (EL) and unexpected losses (UL) of DI Fund.

$$CL = EL + UL$$

where:

- Covered Losses (*CL*) are the losses that need to be covered from the DIF that is constituted by the expected and unexpected losses. It is recommended to estimate the *CL* with the *VaR* methodology.
- Expected Losses (*EL*) can be measured as the average value (mathematical expectation) of loss distribution[12].
- Unexpected losses (*UL*) is the difference between the losses covered from the DIF and the expected losses[13]: $UL = (CL - EL)$.

Although Basel II terminology does not precisely fit the context of DIF adequacy evaluation, it is adopted in this paper in order to underline its consistency with Basel II Accord. In the paper, "default" denotes an insured event (i.e. failure of a DIS member deposit-taking institution).

A. Estimation of Expected Losses (EL)

Expected losses (*EL*) analysis consists of estimation of *insured deposits* in

[12] This approach appears to be the most widespread. In fact, economic provisions (i.e. the part of the DIF used to cover the expected losses) can be quantified under a number of alternative actuarial approaches that take into consideration not only the expected losses (net risk premium), but also a safety loading. For instance, the safety loading can be defined as some multiplier of the standard deviation. An alternative approach is to define the safety loading as a ½-quantile (median) or a fixed level quantile exceeding the median, e.g. upper quartile (¾-quantile). One can also consider expected losses from the managerial and reporting point of view – for instance, see *Treatment of Expected Losses in Capital Calculations* FSA AMA Quantitative Expert Group, 2005.

[13] This approach is consistent with the European Union solvency regime for insurers and reinsurers (Solvency 2). Under the Solvency 2 framework, the insurers should maintain technical provisions to cover expected future claims from policyholders. The technical provisions should be equivalent to the amount another insurer would be expected to pay in order to take over and meet the insurer's obligations to policyholders. The notion of technical provisions corresponds to the notion of Expected Loss adopted in the Guidance. In addition, insurers should maintain available resources sufficient to cover both a Minimum Capital Requirement (MCR) and a Solvency Capital Requirement (SCR). The SCR is based on a Value-at-Risk measure calibrated to a 99.5% confidence level over a 1-year time horizon. Therefore, the SCR corresponds to the total of Expected and Unexpected Loss. The SCR is aimed at covering all risks faced by an insurer (e.g. insurance, market, credit and operational risk) and at taking full account of any risk mitigation techniques adopted by the insurer (e.g. reinsurance and securitisation). The SCR can be calculated using either the Standard Formula or an internal model validated by the national insurance industry supervisor(s).

member banks (i.e. exposure at default - *EAD*)[14], *probability of defaults* (*PD)* of member banks[15] and *share of non-recoverable losses* from the bankruptcy estate of a liquidated bank (i.e. loss given default - *LGD*)[16].

Mathematically *EL* is calculated as the sum of products of EAD, PD and LGD over the whole row of member banks[17]:

$$EL = \sum_i EAD_i \cdot PD_i \cdot LGD_i$$

EAD – insured deposits in a member bank (exposure at default)
PD – probability of default of a member bank
LGD – share of non-recoverable resources from the bankruptcy estate of a liquidated bank (loss given default)

B. Estimation of Unexpected Losses (UL)

Value of unexpected losses (*UL*) *does not have a simple analytical expression*. The easiest way to estimate unexpected losses is to use statistical simulation method (Monte Carlo).

[14] I.e. the amount outstanding in case the bank defaults. In DIF sufficiency analysis context, EAD stands for the volume of insured deposits (the insurer's maximum liability upon failure of a particular member bank).
[15] In case of model with varying maturities, default intensities should be used. In general, default intensity is a more flexible indicator than probability of default.
[16] Which is the percentage of exposure at default that the DIF might eventually lose in case that the bank defaults: *LGD* = 1 – Recovery Rate (*RR*).
[17] It should be pointed out that estimation of DI Fund losses can be obtained from several different levels of aggregation - from using the data on historical losses of the DIS as a whole - to using the data on EAD, PD and LGD in each member bank with appropriate aggregation.

VIII. ESTIMATION OF EXPECTED LOSSES (*EL*) ELEMENTS

A. Estimation of Exposure at Default (EAD)

Credit risk models used by financial institutions, as well as the Basel II Capital Adequacy Accord, generally suggest that exposure at default (EAD) is an exogenous input of the model that is known in advance.

The practice shows that the majority of deposit insurers receive regular reports on insured deposits (i.e. exposure at default), and thus indeed have regular access to the required data.

In short-term forecasting (under one year), a deposit insurer can assume that all defaults occur at the start of the period, and the exposures at default are thus known. However, such assumption can materially distort the forecast for emerging markets that are often characterized by intensive growth in insured deposits. A random distribution of moment of default should be used in such instances, and insured deposits' growth should accordingly be estimated using a stochastic process (time series) model [18]. Further advancement of this element analysis suggests constructing a model that will take into account the interrelation of insured deposit growth on one side and macroeconomic indicators[19] on the other.

For long term forecasting (five and more years) the constant insured deposits (or constant insured deposit growth rate) assumption is quite unrealistic. In order to estimate the long-run exposures at default, statistical models should be combined with scenario analysis approach. Scenario analysis techniques allow one to make forecasts that incorporate both the observed behavior of significant indicators and the expert estimates that take into account the institutional constraints and international experience.

The more complicated issue in expected losses (*EL*) analysis is estimation of loss-given default (*LGD*) and probability of default (*PD*).

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[18] For instance, one can use an autoregression model with a linear or exponential trend. The parameters of this process can be estimated on relevant historical data.

[19] For instance, one can consider such economic indicators as GDP and DI growth, FX rate and discount rate, inflation, unemployment, and average yield and volatility of financial markets.

B. Estimation of Loss Given Default (LGD)

Loss given default (*LGD*) is usually defined as the ratio of losses in the event of default to exposure at default.
In evaluation of DI Fund losses *LGD* is a share of non-recovered resources from the bankruptcy estate of a liquidated bank.

In case of availability necessary data *LGD* can be estimated using various statistical models based on relevant domestic data[20].

Unfortunately foreign data on *LGD* analysis can not be a relevant basis for estimating the loss given default of domestic banks. It is explained by the following. Unlike the failure of a regular enterprise, the default of a bank is a regulatory event. It means that it very much depends on withdrawing banking license in proper time (by the regulator) as well as on the liquidator's experience and other factors of internal banking industry and economic and business environment. So, the differences in national regulatory frameworks and the evolution of national regulatory practice suggest that international experience, as well as observations long passed, is of little relevance for loss given default estimation in a national DIS.

However, the lack of relevant national data on *LGD* statistics in banking sector is also rather typical.

In this case it could be recommended to follow the method based on the foundation IRB approach of Basel II Accord concerning the loss given default on unsecured claims on commercial banks[21]: in case that the deposit insurer has senior claim on recovering resources from failed member banks, it is recommended to assume 45% *LGD*; otherwise, 75% *LGD* should be assumed[22].

In case that lack of relevant data does not allow for adequately accurate estimation of probabilities of default of member banks (e.g. when the probability of default estimation error exceeds 50%), it is recommended to assume zero recoveries (i.e. 100% *LGD*), which would contribute towards a

[20] It is necessary to stress that since the price of a failed member bank's assets and the availability of a liquid market for these assets are contingent on the current and expected economic situation, average loss given default is prone to substantial systematic fluctuations along the course of the business cycle. So the data for LGD analysis should thus be taken at different stages of the business cycle.

[21] See pars. 287-288 of International Convergence of Capital Measurement and Capital Standards: A Revised Framework, Comprehensive Version June 2006 BIS.

[22] There is one more simple approach to estimation of failed bank LGD (*in case of absence relevant data* for more accurate estimation). This approach is based on taking into account the fact that in practice distribution of *LGD* is generally bimodal. It means that more frequently there are 2 main options: the assets of a failed bank are very bad (and in this case *LGD* is close to 1) or the assets are rather good and then *LGD* tends to 0. The intermediate levels of *LGD* are rather rare (because as it was said above very much depends on withdrawing banking license in proper time). In this connection in some situations *LGD* could be taken equal to 50%.

more prudential evaluation of DI Fund sufficiency.

C. Estimation of Probability of Default (PD): Three Main Approaches to Modeling

The existing practice of deposit insurers shows that there can be distinguished three main approaches to modeling the probabilities of default (*PD*) of member banks:

- Standard Approach – on the basis of *credit ratings* of member banks;
- Improved Approach – on the basis of *econometrical* models; and
- Advanced Approach – on the basis of *market data* models.

The main criterion for choosing one of these approaches is the availability and quality of necessary data.

And certainly the best results are achieved by using simultaneously several alternative approaches based on different types of data.

C1. Standard Approach to PD Estimation - on the Basis of Credit Ratings of Member Banks

Correlation of external (independent) or internal credit ratings of member banks and the relevant history of member bank defaults is one of the most obvious and the simplest approach to estimation of probabilities of default (*PD*).

Using independent (external) ratings of member banks is certainly a very attractive solution. However, a substantial part of member banks may not have any independent credit ratings. In this case instead of independent ratings (or in a combination with them) there can be used internal ratings developed by deposit insurers themselves, including - as one of possible options - expert opinions based on results of on-site and off-site examinations of DIS member banks. However, adoption of this approach is associated with substantial costs incurred through engagement of competent experts.

Deposit insurers which use differential premium system can easily use the rating scale of this system for the evaluation of DI Fund sufficiency.

C1.1. Methodology of Credit Rating Approach

Models that estimate default probabilities on the basis of credit ratings are founded on a *mapping procedure* that allows one to estimate the relationship between a discrete credit rating and a continuous probability of default. The simplest mapping approach is to assume that a member bank's probability of default equals the historical average frequency of default of banks with the same credit rating.

There are the two most common ways of mapping credit ratings to probabilities of default - Cohort analysis and Duration analysis.

Cohort analysis is the simplest method to estimate default probabilities when credit ratings are available for a relatively large group of banks. For a given observation period, the probability of banks migrating from one credit rating to another is simply the observed proportion of banks that experience such migration.

Duration analysis accounts for the time spent by the bank in different credit ratings during the observation period. In duration analysis, the migration intensity (probability) is determined as the proportion of years that a bank spent in one rating category before migrating to another rating category divided by the total number of years observed.

It is recommended that the deposit insurers adopt the duration analysis approach, as it allows one to estimate the default probabilities using a smaller sample of banks. Note: the last two paragraphs sound like an IADI guidance (Key point) – как и было задумано.

C1.2. Recommendations for Credit Rating Approach

i. Correspondence of Different Credit Ratings

It should be understood that material differences exist between the methodologies of various rating agencies. Currently, Standard & Poor's is the only one of the three global agencies to assign credit ratings based on pure probability of default. In contrast, Moody's ratings are designed to reflect the expected loss, i.e. the product of probability of default on loss given default. Fitch's ratings have a hybrid nature: prior to default, they reflect the probability of default, while upon default they are aimed at reflecting the expected recovery rate.

Thus, use of mixture of credit ratings issued by two (Moody's and Fitch) out of three global independent rating agencies implies additional (unrealistic) assumptions concerning loss given default.

Internal ratings can be regarded as an alternative (or a supplement) to independent credit ratings. The advantage of these ratings is that they can incorporate information that is not available to independent rating agencies, and also that they can be assigned to all DIS member banks. That is why the use of internal ratings could be the most preferable.

ii. Estimation of PD of Each Member Bank

In current practice of some deposit insurers, zero default probabilities are assigned to sufficiently sound member banks. It should be understood that the aim of the DIS is to cover not only the most likely, but also the unexpected loss that can arise under infrequent, yet material scenarios of failure of seemingly sound larger member banks. Thus, by ignoring the probabilities of default of such institutions one can substantially underestimate the target level of the DI Fund.

If robust estimation of average probability of default of highly rated banks is not feasible due to the lack of relevant data, average default probabilities can be estimated using an aggregated group of sound financial institutions[23]. In case that no relevant data is available, the probability of default of such member banks can be set by at a reasonable minimal, yet non-zero, level. Following the recommendations of IRB approach of Basel II Accord, it is advisable that the minimal probability of default of member banks is set at 0.03%[24].

Whatever the way that probabilities of default are estimated, it is advisable to assess the estimation error (for more details see below).

iii. Incorporation of Business Cycle Factor

For any given credit rating, migration (i.e. credit rating change) probabilities vary materially in course of the business cycle. It can also be suggested that this is also true for any other credit ratings. Under no specific assumptions concerning the future behavior of the business cycle, historical average default frequencies should be estimated over a sample of observations made at all stages of the business cycle[25].

Under the long-term scenario analysis approach, some assumptions are made concerning the future behavior of the business cycle over the given time horizon, meaning that the historical average default frequencies should be estimated over a sample of observations made at corresponding stage(s) of the cycle.

vi. Incorporation of Uncertain Averages

From the statistical prospective, the default probability corresponding to a

[23] For instance, when using the average default frequencies corresponding with the independent credit ratings, it can be assumed that all investment-grade credit institutions have an equal probability of default, and this probability of default can be estimated based on an aggregate sample of sound borrowers.

[24] See par. 285 of International Convergence of Capital Measurement and Capital Standards: A Revised Framework, Comprehensive Version BIS, June 2006.

[25]Alternatively, adjustment coefficients accounting for the intensity of defaults currently observed on a global (for instance, see Kamakura Corporation monthly index of global credit quality), national or industrial scale can be used. For instance, this approach is implemented in industry accepted CreditPortfolioView and CreditMetrics models. The general intuition behind these models is that for rating transition matrices resulting from a random variable *X* that measures change in creditworthiness, we assume that *X* can be split into two parts: (1) an idiosyncratic component *Y*, unique to a borrower, and (2) a systematic component *Z*, shared by all borrowers. Broadly speaking, *Z* measures the "credit cycle" that accounts for the values of default rates and of end-of-period risk ratings not predicted (using historical average transition rates) by the initial mix of credit grades. In good years *Z* will be positive, implying a lower than average default rate and a higher than average ratio of upgrades to downgrades for each initial credit rating. In bad years, the reverse will be true. For instance, *Z* can be inferred from separate transition matrices tabulated each year by Fitch, Moody's or Standard & Poor's and develop a method of calculating transition matrices conditional on the inferred value of *Z*.

certain safety rating is a random variable. The use of historical average default frequency as an estimate of default probability corresponding to a certain credit rating results in a lower estimate of payouts variance and, therefore, underestimates the unexpected loss. A more adequate approach to rating-based estimation of default probabilities is to model them as random variables. Under this approach, each safety rating is mapped to a distribution (or an analytical approximation thereof) estimated on historical data, rather than to a historical average default frequency.

Yet another approach to tackle the uncertainty of default probabilities is to incorporate expert opinions into the distributions of random default probabilities. A number of academic publications offer procedures for formal incorporation of expert opinions into distributions of random default probabilities[26].

C2. Improved Approach to PD Estimation - on the Basis of Econometrical Models

Statistical Credit Scoring (or Econometrical) models estimate financial state of a member banks as a function of a combination of its financial parameters (such as capital adequacy, liquid assets, provisions for bad debts and others). The value of this function is modified in *PD* on the basis of available statistics of historical data on defaults of member banks.

The peculiarity of this kind of models is that they estimate the probability of default of not a particular member bank, but of a typical bank characterized by a given set of observed parameters.

C2.1. Methodology of Econometrical Models Approach

In econometrical (statistical credit scoring) models probabilities of default (PD) are typically estimated using such statistical techniques as multivariate discriminant analysis and regression analysis.

Discriminant analysis is a statistical technique used to determine which variables discriminate between two or more pre-defined groups[27]. Specifically, the method tests the statistical significance of the difference between the mean values of the parameter(s) in question between the groups. If the means for a variable are significantly different in different groups, then this variable discriminates between the groups. The more significant is the difference the better is the chosen parameter. Discriminant analysis can employ a single variable or a number of variables.

Regression analysis is used to derive the conditional expectation of probability of default (*PD*) given the known values of the observed parameters.

[26] Formal approaches to incorporating expert opinions into random distributions of financial variables have been widely discussed in academic publications – for details, see Section 1.1 of Literature Overview.

[27] In case of probability of default estimation, two groups need to be considered: 'defaulted Member banks' and 'non-defaulted Member banks'.

This conditional expectation is estimated in such a manner to minimize the deviation between the estimated and empiric values of the explained variable.

C2.2. Recommendations for Econometrical Models Approach

i. Data Adequacy

Econometrical (statistical) models of probability of default (*PD*) should be calibrated over a sufficient sample of relevant default history. Typically, financial reports data of member banks are used as the main explanatory variables of these models. Taking into account the low frequency of member bank failures, observations need to be collected over long periods of time (5-10 years) to derive efficient estimates. However, changes in financial reporting and disclosure standards and the methodologies of calculation of other explanatory variables imply that the economic meaning of the explanatory variables can change over time. In this case, the deposit insurer should also adopt a transformation procedure to ensure the consistency of the inputs.

Econometrical (statistical) models of probability of default should be updated on a regular basis, i.e. re-calibrated in consideration of the newly available data. The main problems of these models are the principal changes in the economic environment and also the emergence of new lines of business and financial instruments that have a substantial impact on the risk profiles of member banks, when no default history reflecting the new environment is available to produce an adequately updated model.

The deposit insurer thus faces two major problems when adopting a econometrical (statistical) model of probability of default: on the one hand, there is the lack of relevant data required to produce efficient (i.e. low variance) estimates; on the other, observations of failures long past are irrelevant for forecasting future bankruptcies. The achievement of a reasonable trade-off between using a larger sample of less relevant data and a smaller sample or more relevant observations is one of the fundamental problems of statistical modeling of probability of default that does not have a universal solution.

When using macroeconomic and banking industry indicators as explanatory variables, the learning sample (i.e. the sample that is used to calibrate the model) should include observations made at different stages of the business cycle[28]. Otherwise, by incorporating such variables into the model one can achieve a formal increase in the statistical indicators of goodness of fit while achieving the same (or even lower) quality of forecast.

ii. Specification of the Model

[28] Ideally, the learning sample should cover several business cycles.

When constructing a statistical (econometrical) model of probability of default, one should take into consideration the non-linear relationship between the explaining variables and the probability of default of member bank. Member bank failure is a complex event resulting from the multidirectional impact of a number of interconnected risk factors, some of which are also either not observable or do not have a direct quantification. As a result, the relationship between the probability of default, on one side, and the explanatory variables, in the other, generally has a complex non-linear character. A number of statistical techniques, such as preliminary clustering of the learning samples, non-linear regression or non-parametric transformation of observed variables[29], as well as principal component analysis applied to the transformed variables (applicable for monotonous relationships).

When developing a statistical (econometrical) model of probability of default, one should find the balance between the goodness of fit to the learning sample, on the one hand, and model robustness and interpretability of the outputs, on the other.

C3. Advanced Approach to PD Estimation - on the Basis of Market Data Models

In this approach *PD* is estimated not on the basis of previous history of defaults of similar member banks but taking into consideration current state of ***each real member bank*** in current conditions of banking sector and economy as a whole. Market prices of equities and bonds issued by member banks (usually by the biggest ones) reflect the market participants' expectations of the member bank's future performance that are based on all available information.

PD of biggest banks which are the most dangerous and which make a major contribution to the unexpected losses (*UL*) of the DI Fund can be adequately estimated *only on the basis of market-data models*.

The lack of sufficient default history of biggest banks resulted by the low frequency of their failures obstructs efficient statistical (econometrical) estimation of their probabilities of default. In addition to that, material differences exist in the risk profiles of biggest and smaller member banks. Thus there are no universally appropriate methods to extrapolate the results of econometrical (statistical) analysis of default history of smaller member banks on the biggest member banks.

Additionally it is necessary to stress that market data models can be used to calibrate statistical models and/or be incorporated into these models as additional explanatory variables.

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[29] such as logit and probit regressions.

C3.1. Methodology of Market Data Models Approach

In practice, two main types of market data models are the most developed:

- *Structural Model* where *PDs* are estimated on the basis of current market prices of *equities* issued by member banks.
- *Reduced Form Model* where PDs are estimated on the basis of current market prices of *bonds*, issued by member banks.

i. Structural Models

Structural models of credit risk are built around the option pricing theory of Black-Scholes and Merton. In this framework, the default process of a bank (or any other type of company) is driven by the value of the bank's assets and the risk of a default is explicitly linked to the variability of the bank's asset value. A default occurs when the value of a bank's assets (the market value of the bank) is lower than that of its liabilities[30]. For this reason these models are also know as "firm value approach".

These models are more appropriate for qualitative, rather than quantitative analysis.

ii. Reduced Form Models

Unlike structural models, reduced form models do not condition default on the changes of the market value of the bank. Also, unlike other default models, these models estimate default intensities, i.e. instant probabilities of default over an infinitely small period of time, rather than probabilities of default over a given time horizon. Reduced form models introduce separate explicit assumptions on the process of a banks (or any other type of borrower) default intensity. The parameters of this process are specific for each bank-borrower and are derived from the credit spreads corresponding to the issued debt instruments (e.g. bonds) of a given bank-borrower[31]. Default intensity process is modeled separately from the bank's capital structure, asset volatility and leverage.

Reduced-form models imply that at least the upper bound of probability of

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[30] The probability of default is defined as the probability that upon debt maturity, a firm's asset value will be below some threshold level (typically, the value of its liabilities). Since the market value of a firm's debt capital is not directly observable, it is typically estimated based on some theoretical option pricing model, where market value of a firm's equity can be directly view in the mark-to-market quote. To ensure the existence of analytical solution, additional simplifying assumptions concerning the capital structure of the firm are typically made. Other approaches to defining the probability of default exist in theoretical literature - see Section 1.2.3 of the Literature Review.

[31] The available quotes for certain derivative financial instruments (such as credit default swaps) can also be used.

default can be inferred from the spreads on the bank's debt instruments (bonds)[32]. As these yield spreads reflect the market's opinion of the borrower's solvency, the estimates of probabilities of default derived from reduced-form models adjust to changes in borrowers' solvency more quickly than credit ratings or credit score (econometrical) models.

C3.2. Recommendations for Market Data Models Approach

Practical implementation of market data models is largely based on the use of advanced models and techniques of financial theory and stochastic analysis[33]. In this section the more general recommendations are presented.

Successful implementation of market data approach depends first and foremost on the data quality. Market data models rely on the efficient financial markets hypothesis that assumes perfect liquidity of all financial instruments. In practice, the prices of financial assets can include a substantial liquidity premium in addition to credit risk premium. Separation of these two premiums is a non-trivial problem that does not have a universal solution[34]. The standard market data models can thus be inapplicable to emerging economies with insufficient information and low liquidity of the financial market.

D. Back-Testing of Models

In order to ensure comparability of results of PD estimation on the basis of different types of models these models should be constantly tested on historical data (i.e. back-tested). The back-testing should be performed on a control samples that does not overlap with any of the learning samples[35].

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[32] It should be observed that reduced form models (as well as structural models) estimate risk-neutral, rather than real world default intensities. Probabilities of default derived from credit spreads are risk-neutral estimates that include a risk premium. At the same time, statistical estimates of probability of default do not include a risk premium, since they are based on historical data. The problem of conversion of risk-neutral probabilities of default into real world estimates does not have a universal solution and is widely discussed in theoretical literature - see section 1.2.3.2 of Literature Overview for details.

[33] For details see, for instance, Bennett, R.L.; Nuxoll, D.A.; Jarrow, R.A.; Fu, M.C.; Huiju Zhang *A loss default simulation model of the federal bank deposit insurance funds* Proceedings of the Winter Simulation Conference, 4-7 Dec. 2005. This paper discusses a simulation model that is used in a martingale valuation approach to measure and value the risk of the FDIC deposit insurance funds. To evaluate the FDIC portfolio of insurance policies, the model evaluates the insurance policies for depositors at each individual bank and aggregates to obtain the risk of the entire portfolio. To adequately model the risks associated with credit, interest rate, deposit growth, and loss rate, a multidimensional system is formulated. The risk measurement and valuation results are based on Monte Carlo simulation of the system risks.

[34] For more detail on risk premium decomposition see Section 1.2.3.2. of the Literature Overview.

[35] Such indicators as the proportion of type I and type II errors at different cut-off levels or the ratios of the average default probabilities estimated over the test samples to

The test sample structure should reflect the deposit insurer's expectation of the banking sector performance over the given planning horizon. A random sample of observations made at different stages of the business cycle (or ideally, across several business cycles) can be regarded as a starting point.

E. Correlations, Business Cycle and Type of Economy

In the process of evaluation of DI Fund sufficiency correlations of member bank defaults, stage of the business cycle and the type of economy (market or transitional, developed or emerging, etc.) should be taken into account in the course of estimation of every relevant parameter.

When making the analysis of DI Fund sufficiency, failures and recoveries should be regarded as dependent random variables. Under the basic method, the conditionally independent defaults approach of Basel II Accord should be used[36]. Under this approach the change in aggregated index of industrial and/or macroeconomic variables over the course of the business cycle results in simultaneous changes in all probabilities of default. The degree of change for a given member bank depends on its individual sensitivity to the common risk factor.

Under the advanced method, different approaches to default correlation modeling can be developed[37].

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historic default frequencies can be used as the model comparison criteria represented graphically with a Lorentz curve (a.k.a. ROC-curve)

[36] Basel II Accord assumes a fixed relation between the probability of default and correlation of differentials of asset values of borrowers.

[37] E.g. bucketing (peer grouping) of member banks under the assumption of equal and constant default correlation within the groups and zero default correlation between the groups.

IX. CONCLUSION AND SUMMARIZING KEY POINTS

This Discussion Paper presents the IADI recommendations on procedures and methods of evaluation of DI Fund sufficiency on the basis of risk. These recommendations are founded on the best practice of IADI members, as well as the economic logic of the guidelines of Basel Committee on Banking Supervision (Basel II Capital Accord) and the European Union standards of insurers' solvency assessment (Solvency II).

The aim of the Discussion Paper is to provide practical recommendations on short-term assessment of DI Fund sufficiency in a manner that is completely consistent with the IRB approach of Basel II Accord.

In this concluding section the Key Points underlying the more detailed discussion above are provided.

Key Point 1

The main stream in evaluation of financial reserves sufficiency (on the basis of risk analysis) exist

1. In banking sphere there exist recommendations on evaluation of banking capital sufficiency – Basel Principles (based on risk analysis).

2. In insurance business there exist recommendations on evaluation of sufficiency of insurance company reserves – Solvency 2 /Proposal on European Parliament and Council Directive on the Business of Insurance and Reinsurance/(based on risk analysis).

In accordance with this Main Stream the recommendations on evaluation of DI Fund sufficiency on the basis of specific DI risk analysis should be developed.

Key Point 2

Preliminary remarks, important for evaluation of DI Fund Sufficiency

1. DI Fund should be sufficient for serious difficulties in banking sector but *not for systemic banking crisis*.

In systemic crisis Deposit Insurer should be supported by external sources of funding (state budget, etc.). It means that DIF should have a reasonable upper limit which is determined by the definition of "systemic banking crisis".

2. *Deficit of DI Fund* should not mean termination of a DIS functioning.

Under certain conditions maintaining negative balance of DIF can be more reasonable than extraordinary financing of DI Fund from state budget, issuing of debt instruments or charging extraordinary premiums from member banks.

3. DI Fund sufficiency should be taken *in the context of a moving target*.

Movement in deposit liability requires the constant review of DI Fund sufficiency at different intervals.

Key Point 3

Two basic methods of evaluation of DI Fund sufficiency (in practice)

1. On the basis of *expert opinions* on sufficient size of DI Fund (without

estimation of *PD* of member banks and DI Fund cover losses).

2. On the basis of *risk analysis* (on the basis of *PD* of member banks and DI Fund cover losses).

Key Point 4

Three conceptually important issues in evaluation of DI Fund sufficiency on the basis of risk analysis

1. Estimation of expected and unexpected losses of DI Fund
2. Excluding "too big to fail" banks from the basis of evaluation of DI Fund sufficiency
3. Orientation on the implied level of DIS financial reliability (of DI Fund deficit probability)

Key Point 5

Estimation of expected and unexpected losses of DI Fund

The concept of Basel II principles directs the Deposit Insurers on using Value-at-Risk indicators (*VaR*) in evaluation of DIS risks.

It means that a DI Fund should be sufficient to cover both expected ***(EL)*** and unexpected losses ***(UL)***.

$$CL = EL + UL$$

The value of expected losses *(EL)* is determined by actual internal risks of member banks. Unexpected losses *(UL)* show, which deviation of losses from their expected value can be *with a certain probability*.

Thus, the value of unexpected losses *(UL)*, besides economic factors, depends also on the level of financial reliability *which is reasonably preset by a Deposit Insurer* in accordance with current conditions of economy and banking sector.

The question *how to preset this level of reliability* is one of the most important and difficult ones. Its decision is connected with the *implied level of financial reliability* (see Key Point 8).

Key Point 6

Excluding "too big to fail" banks from the basis of evaluation of DI Fund sufficiency

In the majority of banking systems insured deposits are concentrated in a limited number of biggest banks. A failure of even one of such banks can exhaust the DI Fund completely. Therefore, a Deposit Insurer can reasonably expect that in case of instability in any biggest bank the Regulator will implement extraordinary measures to normalize the situation.

In this connection for the purposes of evaluation of DIF sufficiency there should be developed *a methodology for determining the list* of banks which are "too big to fail". These banks *should be excluded from the basis of evaluation* of DI Fund sufficiency.

Key Point 7

Orientation on the implied level of DIS financial reliability

According to the concept of Value-at-Risk (*VaR*) a sufficient level of a DI Fund should correspond to a certain level of financial reliability of Deposit

Insurer.

A *general indicator* of the level of financial reliability *is a credit rating*.

It does not mean that a Deposit Insurer should receive a credit rating from any independent rating agency. It should be a modeling or so-called *"implied" credit rating of a Deposit Insurer*.

Implied credit rating can be assigned with the help of *mapping procedure* which gives the correspondence between credit ratings and the values of probability of default.

Key Point 8

Assigning the implied level of DIS financial reliability (i.e. the implied level of DI Fund deficit probability)

It is deemed reasonable that the level of DIS financial reliability *should not be lower* than the *credit ratings* of the most safe and sound member banks.

On the other hand, it is not rational *if a DIS reliability exceeds the sovereign credit rating* in particular the credit rating of national government debt obligations.

It means that the target level of DIS reliability (i.e. the target level of DI Fund deficit probability) *should lie somewhere between these two values*.

Key Point 9

Two independent tasks in evaluation of DI Fund sufficiency

1. *Short-term* evaluation of DIF sufficiency (horizon not longer than 1 year).

Some simplifying assumptions concerning stationarity of DIS parameters can be applied.

2. *Long-term* evaluation of DIF sufficiency (horizon more than 1 year).

Simplifying assumptions are not applicable. Methods of scenario analysis should be used.

Key Point 10

Long Term Evaluation of DI Fund Sufficiency

The most adequate approach to long-term DIF targeting is to use a dynamic DI Fund balance model. The dynamic balance equation of the DI Fund can be represented as:

$$\boldsymbol{B}_t = \boldsymbol{B}_{t-1} - \boldsymbol{D}_t + \boldsymbol{I}_t + \boldsymbol{P}_t + \boldsymbol{R}_t,$$

where

$\boldsymbol{B}_t$ denotes Fund's balance at the end of period t,

$\boldsymbol{D}_t$ denotes the total payout to depositors over period t,

$\boldsymbol{I}_t$ denotes the investment income of the Fund over period t,

$\boldsymbol{P}_t$ denotes the insurance premiums received over period t,

$\boldsymbol{R}_t$ denotes the recoveries received over period t.

The forward distribution of the Fund balance value can be transformed into a distribution of the Fund's present value using an appropriate interest rate term structure.

Since forecasts are typically based on extrapolation of past dependencies, long-term evaluation of DIS solvency should be based on a number of realistic scenarios that take into account the possibility of future changes in the currently observed tendencies.

Key Point 11

Approaches to estimations of expected (EL) and unexpected losses (UL) of DI Fund

1. Expected losses (*EL*) analysis consists of estimation of *insured deposits* in member banks (*EAD*), *probability of defaults* (*PD)* of member banks and *share of non-recoverable losses* (*LGD*).

$$EL = \sum_i EAD_i \cdot PD_i \cdot LGD_i$$

EAD – exposure at default - insured deposits in a member bank

PD – probability of default of a member bank

LGD – loss given default - share of non-recoverable resources from the bankruptcy estate of a liquidated bank

2. Value of unexpected losses (*UL*) *does not have a simple analytical expression*. The easiest way to estimate unexpected losses is to use statistical simulation method (Monte Carlo).

Key Point 12

Approaches to estimation of Exposure at Default (insured deposits)

The majority of Deposit Insurers receive regular reports on insured deposits (i.e. exposure at default) and thus have regular access to the required data.

In short-term forecasting it can be assumed that all defaults occur at the start of the period and insured deposits (exposure at default) are thus known.

For long-term forecasting of insured deposits (exposure at default) statistical models should be combined with scenario analysis approach.

Key Point 13

Approaches to LGD estimation

In evaluation of DI Fund losses *LGD is a share of non-recoverable resources* from the bankruptcy estate of a liquidated bank.

In case of availability of necessary data *LGD* can be estimated on the basis of *various statistical models*.

In case of absence of relevant data several approaches to LGD estimation could be recommended:

- on the basis of IRB approach of Basel II Accord concerning the LGD on unsecured claims of commercial banks – *depending on priority of a Deposit Insurer claim in bankruptcy procedure* LGD could be taken equal to 45% or 75%;

- on the basis of generally bimodal distribution of LGD in practice – in this connection as one *of the most simple approach* it could be recommended to set LGD equal to 50%

- *in the instances* when probabilities of default cannot be estimated with adequate accuracy (possibly due to the lack of relevant data), it is recommended that *a 100% constant LGD* is adopted to ensure a prudential evaluation of DI Fund sufficiency.

Key Point 14

Three main approaches to estimation of probability of default (PD) of member banks

1. Standard Approach – on the basis of *credit ratings* of member banks
2. Improved Approach – on the basis of *econometrical models*
3. Advanced Approach – on the basis of *market data models*

The *main criterion for choosing* one of these approaches is the *availability of necessary data*.

The *best results* are achieved by using *simultaneously several alternative approaches* based on different types of data.

Key Point 15

Standard Approach to PD estimation - on the basis of credit ratings of member banks

Use of *independent ratings is a very simple solution* however substantial part of member banks may not have any independent credit ratings.

In this case instead of independent ratings (or in a combination with them) *there can be used internal ratings* developed by Deposit Insurers themselves, including the expert opinions based on results of on-site and off-site examinations of member banks.

Deposit Insurers which use *differential premium system* can *easily use the rating scale* of this system for evaluation of DIF sufficiency.

A *mapping procedure* is used *for transformation of ratings into values of PD*.

Key Point 16

Improved Approach to PD estimation - on the basis of econometrical models

In econometrical models financial state of the member banks is estimated as a *function from the combination of its financial indicators*.

The value of this function is modified in *PD* on the basis of *available statistics of historical data on defaults* of member banks.

Key Point 17

Advanced Approach to PD estimation – on the basis of market data models

PD is estimated not on the basis of previous history of defaults of similar member banks but taking into consideration current state of *each real member bank* in current conditions of banking sector and economy as a whole.

PD of biggest banks which are the most dangerous can be adequately estimated only by market data models.

In practice, two main types of market data models are the most developed:

- *Structural Model* - *PDs* are estimated on the basis of current market prices of *shares* issued by member banks.

- *Reduced Form Model* - PDs are estimated on the basis of current market prices of *bonds*, issued by member banks.

Key Point 18

Taking into account correlations, business cycle and type of economy

Correlations of member bank defaults, stage of the *business cycle* and *type of economy* (market or transitional, developed or emerging, etc.) *should be taken into account* in estimation of any parameter in evaluation of DI Fund sufficiency.

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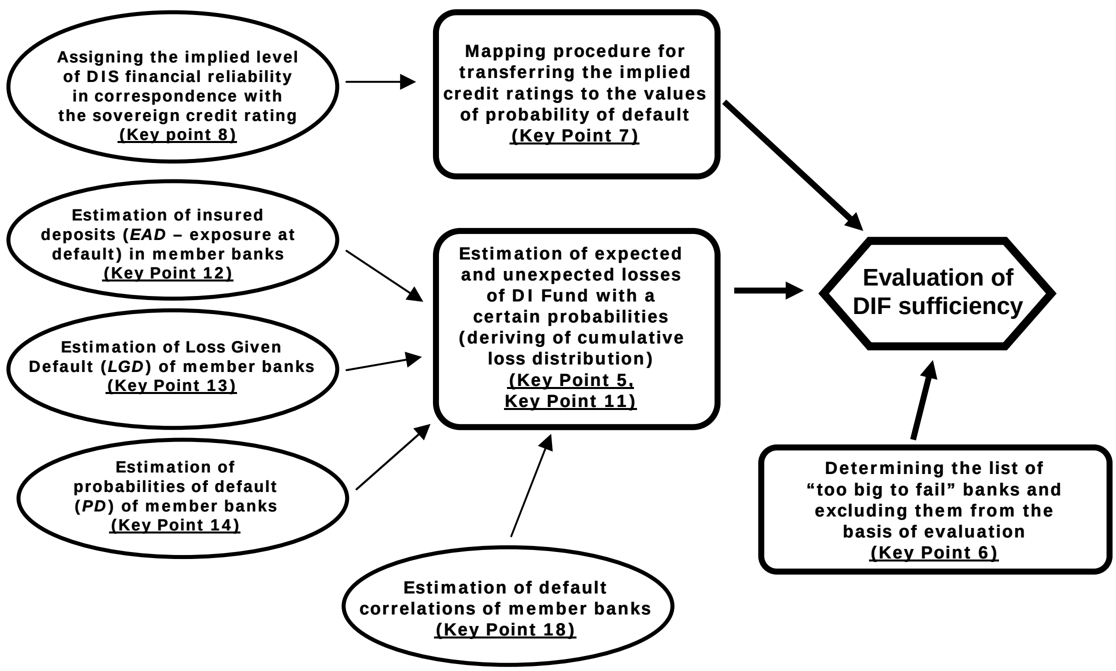
XI. APPENDIXES

Appendix 1. ***Procedures of evaluation of DI Fund sufficiency on the basis of risk analysis***

Figure 1: Procedure of Short-Term DI Fund Sufficiency Evaluation



Section A. *Short-term DI Fund Sufficiency Evaluation Procedure*

1. Following Key Point 8, determine the implied level of the DI System financial reliability in correspondence with the sovereign debt credit rating.
2. Following Key Point 7, transfer the implied solvency level of the DI System to the probability of default value using the corresponding mapping procedure.
3. According to Key Point 5 and Key Point 11, estimate expected (*EL*) and unexpected losses (*UL*) of DI Fund *with a certain probabilities* (derive the DI Fund cumulative loss distribution):
   3.1. estimate the volume of insured deposits (*EAD*) in member banks (according to Key point 12);
   3.2. estimate loss given default (*LGD*) of member banks (according to Key Point 13);

3.3. estimate probabilities of default (*PD*) of member banks (by 1, 2 or 3 methods as it is shown in *Figure 2, Section B* below) (according to Key Point 14);

3.4. estimate default correlations of member banks (according to Key Point 18);

3.5. derive the DI Fund cumulative loss distribution following the relevant procedure.

4. Following Key Point 6, work out a list of too-big-to-fail banks that should be excluded from the basis of evaluation.

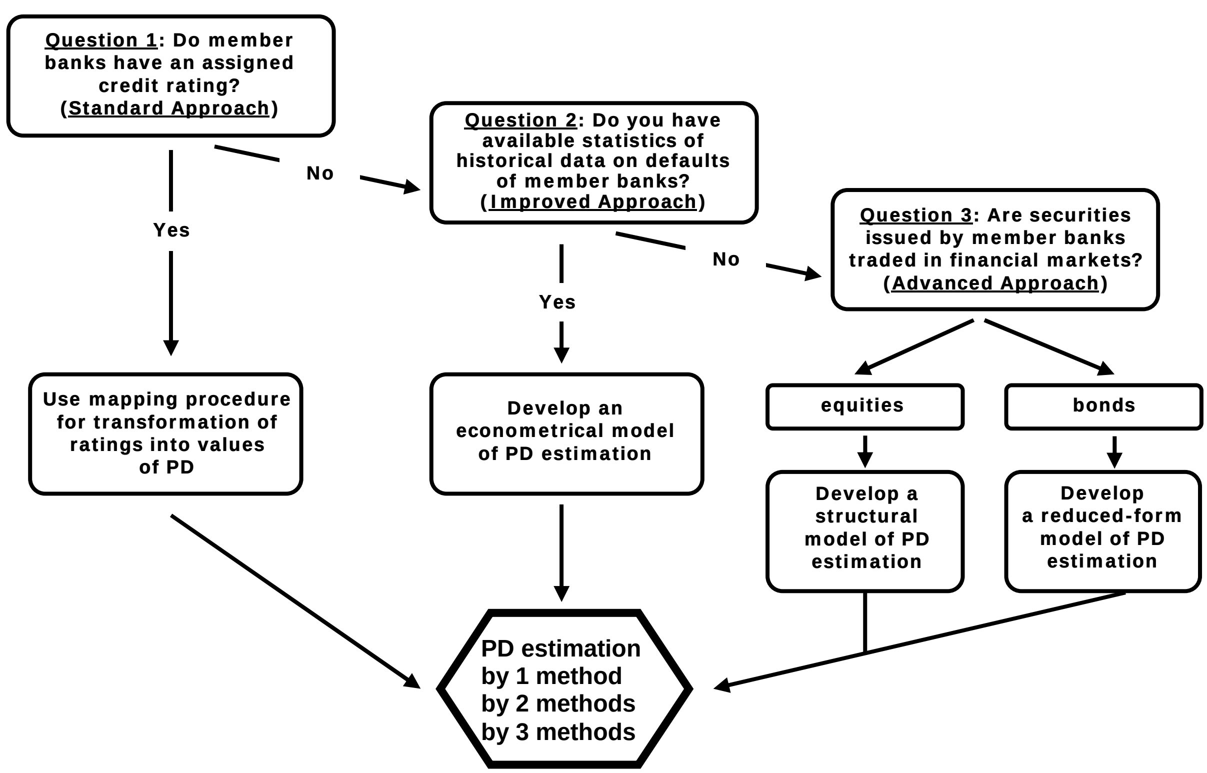
5. Summing up all above proceeding stages, evaluate DIF sufficiency.

Section B. *Member Bank Probability of Default Estimation Procedure*

It should be stressed that:

- The best results are achieved by using simultaneously several alternative approaches based on different types of data.
- The main criterion for choosing one of these approaches is the availability of necessary data.

Figure 2: Probability of Default Estimation Procedure



__Appendix 2.__ Existing Practices of Deposit Insurers on Risk Analysis and DI Fund Sufficiency Evaluation

As a part of work on development of this Discussion Paper there was conducted a survey of deposit insurers' approaches and practices in the areas of deposit insurance funds sufficiency estimation and financial risk analysis. Available publications on risk evaluation by deposit insurers for the purposes of DIF sufficiency estimation and forecasting were also studied.

There were received 33 responses to the especially distributed questionnaire[38]. Ten deposit insurers[39] indicated that they practice forecasting of DIF losses on the basis of estimation of probability of default for member institutions (*see* *__Table__* *below*), 17 respondents noted that they use targeting for their deposit insurance funds (in 16 cases set as a ratio of the balance of the Fund/Fund's assets to total insurable or insured deposits (insurance liability), in one case – in the Philippines - the target for the fund is not a ratio but an amount that is estimated annually). Among respondents, 10 use risk analysis for differentiating banks for premium assessment purposes as they have differential insurance premium systems.

	Country	**Statistical models based on historical data**	**Internal ratings**	**Expert judgement**	**External ratings**
	Canada	+	-	-	+
	Hong-Kong	+	+	-	+
	India	+	-	+	-
	Indonesia	**+**	**+**	**-**	**-**
	Nigeria	+	+	-	-
	Russia	+	-	-	-
	Philippines	-	+	+	+[40]
	USA	+	+	+	+[41]
	Singapore	+	-	-	+
	Zimbabwe	-	-	+	-
10	*Total*	**8**	**5**	**4**	**5**

[38] Argentina, Bahamas, Brazil, Bulgaria, Canada, Czech Republic, France, Hong-Kong, Hungary, India, Indonesia, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Mexico, Nigeria, Peru, the Philippines, Russia, Romania, El Salvador, Singapore, Sweden, Taiwan, Tanzania, Trinidad and Tobago, Turkey, Uruguay, USA, Venezuela and Zimbabwe.

[39] Canada, Hong-Kong, India, Indonesia, Nigeria, Russia, the Philippines, USA, Singapore and Zimbabwe.

[40] Are used in PDIC's internal rating system.

[41] Not used for purposes of reserving, but used in differential premium system – for largest banks.

The Survey results show that for estimation of probability of default (PD) deposit insurers usually use statistical models based on historical data (Canada, Hong-Kong, India, Indonesia, Nigeria, Russia, USA, Singapore).

In **Canada** additionally to historical data statistical model CDIC uses so called Discretionary Analysis for the purpose of assessment the extent to which the DI Fund target would satisfy established requirements. The Discretionary Analysis also assesses the reasonableness of estimations based on the Monte Carlo methodology. Besides this CDIC (Canada) uses external ratings[42].

In **Hong-Kong and Singapore** the external ratings are also used in addition to mathematical models.

In **India** actuarial valuation of the DICG Corporation's liability is used which is also based on the historical failure rate – for this purpose the Corporation hires external actuary.

In **Indonesia** IDIC assigns an internal rating for each member bank based on its CAEL (Capital, Assets Quality, Earnings, and Liquidity) estimation, then calculate each member bank's PD using a model based on the internal rating transition probability matrix.

In **Nigeria** in addition to statistical models also internal ratings (CAMEL) are used.

In **Russia** additionally to statistical (econometrical) model there is also used the reduced form model (structural model) based on the market prices of securities (in particular bonds) issued by member banks. The final result is received as an integral combination of both models outcomes.

PDIC (**Philippines**) for estimating probability of default of member institutions uses internal ratings (Offsite Bank Rating Model – similar to CAMELS but it excludes element M - Management) and expert judgement (consultations of the PDIC Management with the central bank).

In **USA** besides historical data statistical model the FDIC also uses internal ratings (CAMELS) and expert judgment (Financial Risk Committee) [43]. External ratings are used for setting premium rate for largest banks. As an additional model the FDIC uses Loss Distribution Model (LDM) based on forecasting member banks tangible capital and failure-related losses that in accordance with economy and banking industry condition.

In **Zimbabwe** the expert judgment of the central bank's examiners and CAMELS ratings assigned to banks by the central bank of Zimbabwe are used.

According to the received responses currently a number of deposit insurers is working on the development of new models for forecasting losses from possible failures of member institutions. Thus Nigeria noted that it is developing a reduced form model for future implementation, El Salvador is

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[42] In Canada PD for each institution is developed based on a weighted average of Moody's, S&P and Moody's KMV ratings. The PD assigned to each member is based on the default frequency associated with the member's respective credit rating. The overall PD developed by CDIC is the weighted of using 75% S&P and Moody's data and 25% using KMV Expected Default Frequency data.

[43] In the USA probability of default is estimated only for institutions with CAMELS ratings of 4 or 5 (the two highest risk supervisory ratings).

planning to implement statistical models based on historical data as well as internal ratings.

As to the models and methodologies for calculating Loss Given Default, 12 respondents noted that they do forecast this factor. In Canada, Indonesia, Mexico, Russia, Singapore, Venezuela and USA deposit insurers utilize for these purposes historical data about losses. In Hong-Kong, Kazakhstan, El Salvador, Taiwan and Zimbabwe for forecasting LGD deposit insurers use estimations mainly of expert nature.

For verification of results of mathematical modeling a number of deposit insurers use back testing and stress testing. Among these are deposit insurers from Hong-Kong (stress testing), Russia, Singapore and USA.

The majority of respondents noted that they calculate target reserve ratio of DI Fund. The value and definition of DIF target ratio differs substantially (*see Table below*).

Country	**DI Fund Target Reserve Ratio (%)**	**Denominator (insurable/insured deposits)**	**Actual value of DI Fund reserve ratio as at 1.01.2007 (%)**	**Who sets the target reserve ratio**
Argentina	5.0	Total (insurable)	0.96	Law
Bulgaria	5.0	Total (insurable)	0.36	Law
Brazil	2.0	Total (insurable)	1.93	Central bank
Canada	0.40-0.50	Insured (insurance liability)	0.34	Board of directors
Chile	Not prescribed		0.36	
El Salvador	1.0	Total (insurable)	1.02	Law
France	Not prescribed		0.10	
Hong-Kong	0.345	Total (insurable)	0.08	Law
Hungary	1.0-1.5	Total (insurable)	1.13	Board of directors
India	Not prescribed	Insured (insurance liability)	0.8	
Indonesia	2.5	Total	n/a	Law
Jamaica	5.0	Insured (insurance liability)	2.17	Board of directors
Jordan	3.0	Total (insurable)	1.20	Law
Kazakhstan	5.0	Total (insurable)	2.11	Law

Nigeria	Not prescribed		10.78	
Peru	Not prescribed		1.86	
Philippines[44]	10.0	Insured (insurance liability)	6.0	Board of directors
Russia	5.0 5.0	Total (insurable) Insured (insurance liability)	1.09 5.20	Law Management board
Romania	1.5	Total (insurable)	0.98	Board of directors
Singapore	0.3	Total (insurable)	<0.3	Law
Sweden	Not prescribed		2.9	
Taiwan	5.0[45]	Total (insurable)	0.16	Law
USA	1.15-1.50	Insured (insurance liability)	1.21	Law
Uruguay	5.0	Total (insurable)	0.24	Management board
Venezuela	Not prescribed	Total (insurable)	10.92[46]	
Zimbabwe	2.0	Total (insurable)	0.98	Management board

As to utilizing the target reserve ratio for measuring DI Fund's sufficiency, according to received responses few countries set this ratio as an interval (USA, Hungary, Canada and Russia) [47]. In most cases it is envisaged that after reaching the target decision can be made about lowering insurance premiums paid by member institutions to the fund, i.e. the target reserve ratio serves as upper limit for deposit insurance funds. From those responded to the questionnaire Hong-Kong, Hungary, USA and Jordan noted that deviation from the target level can lead also to insurance premiums increase.

<u>Appendix 3.</u> Literature Review on Credit Risk Modeling (for the purposes of evaluation of DI Fund sufficiency on the basis of risk analysis) – 65 pages (attached)

[44] The target is set as an absolute figure – it was recalculated as a ratio. PDIC has revised its methodology for determining its insurance reserves target in June 2008. The DI Fund Target for 2009 based on the revised methodology is Philippine pesos 92.5 billion and is 9.3% of insured deposits as of March 2009, while the actual fund level is Philippine pesos 60.5 billion and is 6.1% of insured deposits as of March 2009.

[45] The Deposit Insurance Act was amended in January 2007 stipulating the TRR at 2%.

[46] As at May 2007.

[47] PDIC is currently studying to set the target reserve ratio as an interval.