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IMF Working Paper

Optimal Bank Recovery

by Charles Goodhart and Miguel Segoviano

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Optimal Bank Recovery

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Abstract

Banks' living wills involve both recovery and resolution. Since it may not always be clear when recovery plans or actions should be triggered, there is a role for an objective metric to trigger recovery. We outline how such a metric could be constructed meeting criteria of (i) adequate loss absorption; (ii) distinguishing between weak and sound banks; (iii) little susceptibility to manipulation; (iv) timeliness; (v) scalable from the individual bank to the system. We show how this would have worked in the U.K., during 2007–11. This approach has the added advantage that it could be extended to encompass a whole ladder of sanctions of increasing severity as capital erodes.

JEL Classification Numbers:G21, G28, G33,

Keywords: Bank Recovery, Bank Resolution, Metrics for Triggers, Loss Absorption, Probability of Distress, Loan Default.

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I. INTRODUCTION

The European Banking Authority is currently consulting on standards for bank recovery and resolution planning, (http://www.eba.europa.eu/regulation-and-policy/recovery-and-resolution). Not only are the separate stages of recovery and resolution commonly linked together in discussions of financial regulation and international standards (e.g., the "Key Attributes of Effective Resolution Regimes for Financial Institutions"), but also everyone would prefer that a bank recovers, rather than has to be placed in resolution.

This suggests to us that more emphasis should be placed on the determination of and threshold for, the recovery stage. Whereas there has been much discussion, on triggers for resolution, it may not always be clear when recovery plans or actions should be triggered.[1] The purpose of this paper is to try to fill that lacuna.

First, bankers, if left to themselves, are likely to enter the recovery stage voluntarily far too late. A concern about reputation, should the news leak (reputational stigma), and the likelihood that top management will be overly self-confident in their ability to keep going successfully, (think of Fuld and Goodwin), will combine to make management reluctant to call time on themselves. Second, since there has been little, or no, prior work on deriving a quantifiable metric to signal the trigger for entry into the recovery stage, the intention of this paper is to do so following a systematic scientific approach.

We see our objectives for establishing a metric(s) for initiating the recovery phase as several. First, the metric should capture the adequacy of banks' loss absorption buffers. Second, we want a criterion that distinguishes between weak and sound banks. That is, it captures all (banks) that are facing a serious likelihood of subsequent failure (unless turned around)—i.e., few Type One errors. However, we want that criterion to catch relatively few 'sound' banks, i.e., that would have survived anyway, Type Two errors, (though since recovery is less irreversible than resolution we would give relatively more weight to Type One errors in this trade-off). Third, we would want the metric to embed little susceptibility to manipulation; it should be based on observable, verifiable and objective data. Fourth, we would want the trigger for recovery to occur long enough before continuing problems lead to resolution in order to give those concerned, i.e., the bank managers and their supervisors,

[1] The EBA's Discussion Paper on 'a template for recovery plans (EBA/DP/2012/2), (London, May 15) does ask the banking community (Questions, p. 15), Q7, "How would/do you identify quantitative and qualitative recovery early warnings and triggers? What are the key metrics you would use to develop early warnings and triggers?" Note that such warnings and triggers are, apparently, being left to the banks to decide for themselves, though subject, ex ante, to supervisory approval. This is likely, in our view, to result in an excessive delay in pulling any such trigger. Moreover, the jurisdictional organisation of the recovery stage is not clearly defined. Thus the Basel Committee on Banking Supervision (BCBS) paper on 'Principles for Effective Supervisory Colleges (BIS, June 2014), states, p. 17, that "While CMGs [Crisis Management Groups] are typically responsible for coordinating resolution plans, responsibility for coordination of recovery plans varies across jurisdictions and may be the responsibility of the CMG, the supervisory college, a third body (e.g., a resolution college) or responsibility may be shared."

time and opportunity to turn the bank around before resolution has to take place and fifth since banks are not isolated entities, we would like the methodology to account for extreme losses potentially suffered by vulnerable banks due to the banks' interconnectedness to the system (systemic risk).We discuss in the following sections how this may be achieved.

II. Bank Recovery

The so-called 'Living Wills' of banks have two elements, recovery as well as resolution.[2] Most of the discussion to date has related to the triggers for resolution. But the recovery phase precedes the onset of any need for resolution. Focusing on the timing/trigger for the start of the recovery phase has several advantages. First, it can be done by the application of a more objective metric. The use of accounting measures of capital leads to long delays in the recognition of problems and can be manipulated. It has never been even a good coincident measure of difficulties, let alone an early warning. The advantage of addressing the question of setting an appropriate trigger for the recovery phase is that, somewhat surprisingly, we know of no one else who has done this. There is no accretion of prior received doctrine to dismantle. We can proceed to do this by as scientific a metric as we can derive.

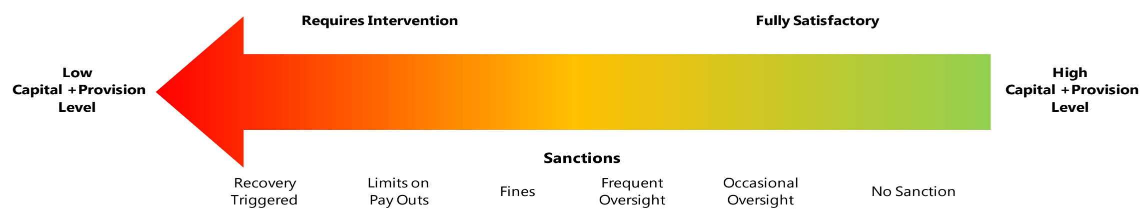
Clearly entry into the recovery phase is a serious business, and quite traumatic for management, if only because there is always a danger that the news may leak, leading to reputational damage. Left to themselves managers would be inclined to defer leaving entry into this phase far too late. On the other hand, because it is a serious step, it should not be initiated until there is a serious chance, without a major change of direction, of subsequent failure. What one wants is a metric which catches almost all banks that are likely to fail, or would have failed without recapitalization (or major surgery) (i.e., almost no Type One errors), and relatively few banks that survived without outside help (some, but not too many, Type Two errors), and does so early enough to give a reasonable chance to turn the business around before failure and resolution become inevitable.

Such a metric has additional advantages. By occurring several months prior to the onset of any resolution, should the latter nevertheless become necessary, it would give supervisors the opportunity and time to work with the bank in difficulties. It could also represent the minimum level at which a (high-trigger) Contingent Convertible Capital Instrument might kick in. On the other hand, because of reputational risk and market manipulation, it would be desirable that the trigger for entry not be publicly observable. While we believe that the *principle* whereby this trigger should be set should be known to all, the actual numerical parameters should be a matter of private discussion between each bank and the supervisor, with the supervisor having the right of determination when there is a dispute.

[2] Technically, these are called recovery and resolution plans (RRP).

We believe that we can construct such a metric and do so in Section III. Such an approach can also be broadened, to construct a ladder of sanctions, as the equity buffer erodes, which we regard as an advantage. Clearly when capital adequacy has fallen to a level which requires the recovery stage to kick in, it is far below desirable levels. There have been studies of the desirable level of equity ratios, which may be defined as the point where the extra social benefits from financial stability are matched, or exceeded, by the extra costs applicable to financial intermediation. These studies, such as Miles, et al. (2013), Admati and Hellwig (2013), suggest that this inflection point may be *much* higher than minimum regulatory requirements, at around 20 percent of risk weighted assets (RWA), or perhaps 10 percent plus of total assets. Be that as it may, the methodology used for assessing the intervention point for recovery, can also be applied to construct a ladder of sanctions, initially mild and becoming more severe, as equity capital adequacy falls towards the recovery trigger. Thus it could run as shown in Figure 1.

Figure 1. Ladder of Sanctions



Source: Author's Definition

III. INTERVENTION FOR RECOVERY

We provided above the economic rationale for developing a framework to characterize an intervention point for recovery, and perhaps a broader ladder of sanctions. In this Section we explain how such a framework can be made operational, following the steps shown in Figure 2.

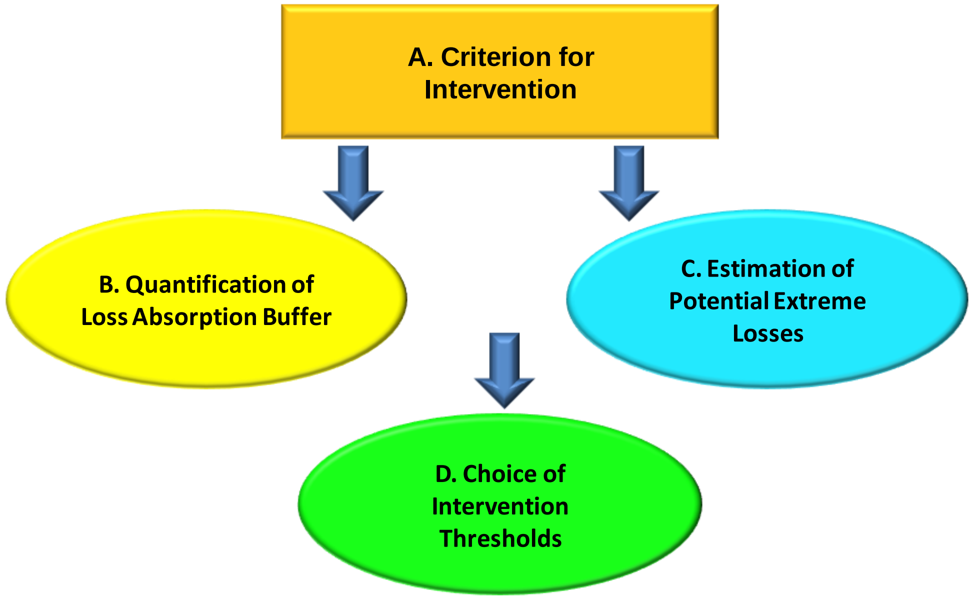
A. Criterion for Intervention

The first question is how to set a criterion to decide which institutions should be subjected to intervention, whether that intervention setting is for recovery or milder forms of intervention.

Our suggestion is to target those institutions whose potential extreme losses could erode their loss absorption buffers. This principle is consistent with the "risk-based" regulatory framework in the Basel Accord, where provisions should serve as a buffer to cover expected losses (EL) and capital should serve as a buffer to cover partially (at least up to a degree of confidence) extreme losses; i.e., unexpected losses (UL). So, the "total" buffer of a bank (provisions + capital) should serve to protect it from potential extreme losses (expected + unexpected); which may be quantified from the loss distribution of a bank in Figure 3.[3]

This leads to two questions. How do we appropriately define loss absorption buffers and potential extreme losses?

Figure 2. Steps to Define Intervention Actions



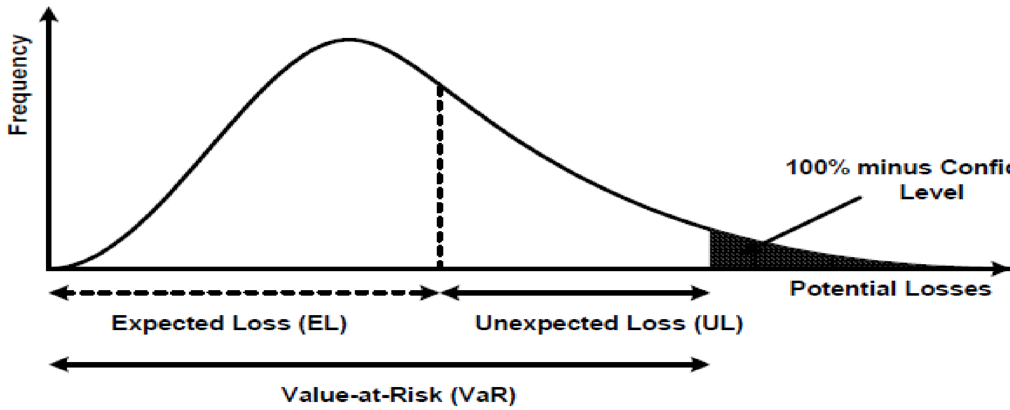
Source: Authors' definition.

B. Quantification of Loss Absorption Buffer

The proper definition of loss absorption buffers requires an adequate definition of "capital". Traditionally, the capital adequacy ratio (CAR), defined as the accounting value of regulatory capital to risk weighted assets (RWA), has been used as a measure of loss absorption buffer. The CAR, however, has lost credibility owing to difficulties in assessing the "true" value of both its numerator and denominator. Problems with using the accounting value of regulatory capital are that it is not clear how to appropriately value different forms of capital, and different accounting rules and/or regulatory definitions that vary across countries. Moreover, it is highly likely that, when an institution becomes financially stressed, the underlying (true) equity already is (severely) impaired, prior to default, well before this becomes recognized in the (published) accounting/regulatory values (due both to lags and various forms of manipulation).

[3] See "An Explanatory Note on the Basel II IRB Risk Weight Functions", Basel Committee on Banking Supervision, July 2005.

Figure 3. Loss Distribution: Expected and Unexpected Losses



Source: Basel Committee on Banking Supervision, July 2005

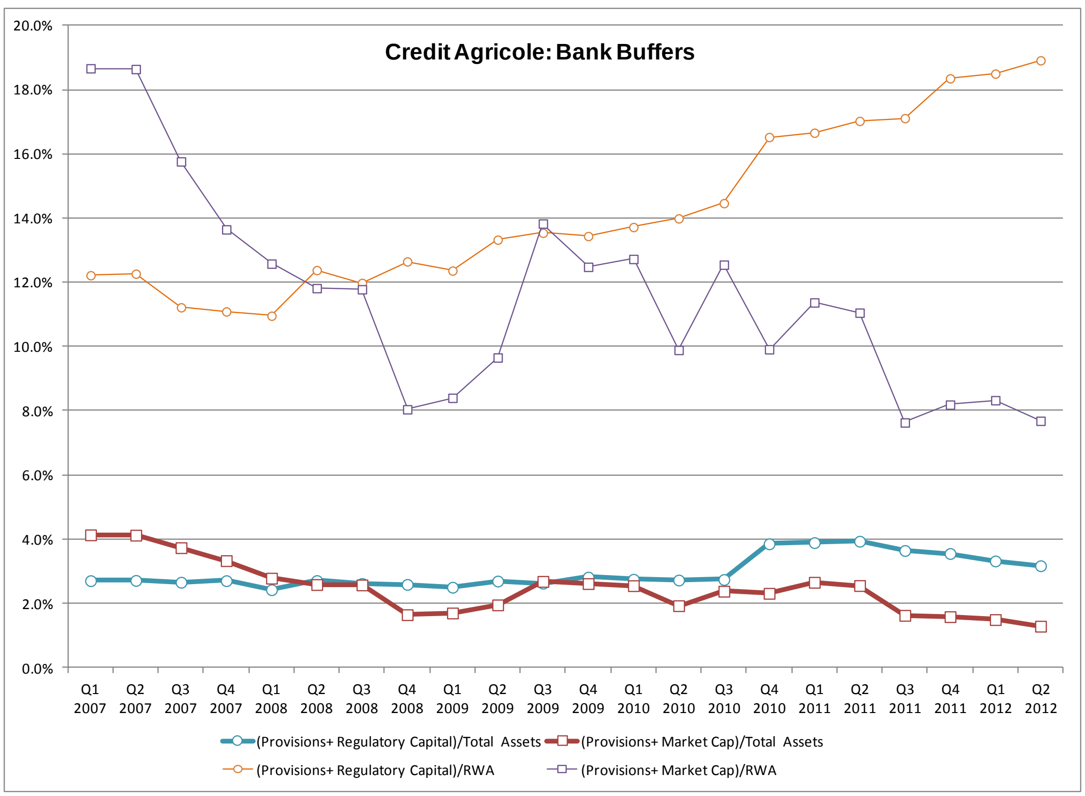
Equally, the accounting value of RWA may be subject to different regulatory definitions in different countries. Manipulation of RWAs has lately been debated by regulators and market analysts, who are increasingly introducing or focusing on leverage ratios (LR), defined as Regulatory Capital/Total Assets, as complementary measures to CARs (partly due to the simplicity of calculating Total Assets) in orders to assess institutions' solvency. The idea is that a combination of CAR and LR should provide banks with adequate incentives to minimize risk while avoiding difficulties in assessing RWAs and allowing an easy comparison across institutions.

With these principles in mind, we propose to use market valuation of equity (Market Cap), as also proposed by Calomiris and Herring (2011). We recognize that equity valuations can be subject to both market over-shoots and (temporary) crashes and, in thin markets, to potential manipulation. In order to mitigate these issues, we suggest using a quarterly moving average of Market Cap. We also propose including regulatory provisions as part of the loss absorption buffer; these are not subject to market over-shoots, and also are usually kept liquid in cash or in low-risk liquid fixed income assets which are less prone to accounting manipulation.[4] Hence, we suggest defining the numerator of the loss absorption buffer as the quarterly moving average of Provisions + Market Cap. Due to the measurement problems with RWA discussed above, we also recommend using Total Assets (TA) as the numeraire of our proposed buffer.

[4] Risk-based regulatory provisions can serve as a powerful micro-prudential tool to constrain excessive credit growth in specific segments; hence, by taking provisions as part of the loss absorption buffer, this could provide incentives for their proper use.

Hence, the risk sensitive loss absorption buffer ratio (RiBuR) defined as [(Provision + Market Cap)/TA] becomes the target ratio; i.e., critical ratio, to identify those institutions that should be subjected to intervention, whether recovery or the preceding milder sanctions. The proposed RiBuR reflects more closely market perceptions of the economic value of equity, while being less subject to accounting manipulation or regulatory arbitrage; hence, it would be a more transparent indicator and easily estimated by regulators, investors, and markets. As an example of how significant differences in loss buffers appear (for a given bank), depending on how such buffers are estimated, Figure 4 shows buffers estimated as (Provisions + Regulatory Capital) and (Provisions + Market Cap) as percentage of TA and RWA. First, the buffers estimated as a percentage of TA are significantly smaller than buffers divided by RWA. Independently of the numeraire employed, buffers employing Market Cap react faster to periods of distress because they reflect more closely market perceptions of the economic value of equity.

Figure 4. Loss Absorption Buffers in Terms of Risk Weighted Assets and Total Assets



Source: Authors' calculations, Datastream and Bloomberg Data.

C. Estimation of Potential Extreme Losses

In order to quantify the potential extreme losses that a bank can have at specific points in time, we need to estimate the loss distributions of the bank at each period of time.

This distribution provides information of the losses that a bank can have and their probability of occurrence. Hence, the mean of this distribution represents "expected losses" (EL) and by focusing on high percentiles of this distribution, it is possible to quantify extreme (high) losses up to a confidence level (Figure 3). In order to estimate banks' loss distributions, we followed the following steps:

- Characterization of banks' distress probabilities.
- Quantification of losses.

Characterization of Probabilities of Distress

Probabilities of distress (PoDS) for a bank can be estimated using different approaches. The most common methods include PoDs extracted from credit default swaps (CDS), the Merton model, and various other methodologies available in the market. In this paper we use the Merton approach to estimate banks' PoDs. Our choice for this approach was mainly based on data availability and quality for the sample of banks under analysis. Note that our intention in this paper is to illustrate how our proposed framework to define recovery thresholds can be implemented; irrespective of the approach used to estimate banks' PoDs.

The suitability of specific PoD approaches depends on the combination of (i) theoretical modeling frameworks and assumptions (under the different approaches) and (ii) the type and quality of data available in each financial system. Hence, the choice of the best approach for specific jurisdictions should be determined by the relevant local authorities, who should have detailed knowledge of data availability and quality and the characteristics of their financial systems.[5]

Quantification of Losses

Once PoDs for each bank have been defined, it is possible to use alternative approaches to quantify banks' potential losses and generate their loss distribution. In general, we can group these approaches into two types, "closed form" or "non-closed form". The first comprises various frameworks, including the Vasicek model and Credit Risk +. The latter comprises the Structural Approach (SA), which embeds different parametric and non-parametric methodologies.[6] These approaches differ significantly in their theoretical foundation, assumptions and data requirements. Therefore, our suggestion would be that the relevant local authorities determine the most appropriate framework for their jurisdictions, based on

[5] Although we made sure that the basic data quality criteria were satisfied and checked for consistency of results when choosing the Merton approach, it was beyond the scope of this paper to make a rigorous theoretical and empirical analysis of each of the possible approaches to estimate banks' PoDs in order to define the best approach under each jurisdiction.

[6] Parametric methodologies under the SA include the Credit Metrics framework (RiskMetrics, 1997). Non-parametric methodologies include the CIMDO approach (Segoviano, 2006).

data availability, data quality and the authorities' view on the theoretical advantages and disadvantages of the alternative approaches.[7]

For this paper, we decided to quantify losses under two alternative approaches, the Vasicek approach and the CIMDO-approach (threshold approach), a non parametric SA. The Vasicek approach was chosen mainly due to its theoretical simplicity; however, this simplicity entails a cost, that the key assumptions of the model may fail to hold; hence, its use carries a high risk of lack of robustness and inconsistency of results.

The CIMDO approach was chosen for two main reasons. First, this model offers the possibility of accounting for systemic risk; i.e., the contagion that one bank can pose on other banks in the system (which we consider a key advantage for assessing financial stability). Second, this is a non parametric model; so, it is based in fewer assumptions; therefore, it is more robust in the presence of limited data, which most authorities would likely face when trying to define/identify intervention thresholds.[8] However, the CIMDO approach involves a more complex theoretical framework.

Nevertheless, once PoDs for individual banks have been estimated, both approaches are relatively simple to estimate. Below we briefly describe these approaches and present the empirical results of the analysis. Parts of this description, especially of the CIMDO approach, are inevitably somewhat technical. So those readers prepared to take such technicalities on trust, might want to skip through to Section "Empirical Results", where we present our empirical results.

Quantification of Losses under the Vasicek Approach

This approach is employed by the Basel regulatory framework to model explicitly (in closed form) the default rate of loan portfolios, then to estimate the portfolios' loss distributions and from these, to quantify their regulatory capital (at the 99.9 percentile of the loss distribution).[9] This approach can be briefly described in the following three steps:

(i) **Characterization of the log asset return.** The log asset return of a firm is assumed to depend on a factor that reflects the state of the economy and an idiosyncratic component. Thus, implied log asset returns and the probability of default p_i for each type of loan i, are conditional on the state of the economy.

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[7] A rigorous analysis and comparison of theoretical advantages/disadvantages of these approaches is beyond the scope of this paper; however, a useful reference is Schuermann and Hanson (2004).

[8] Under the probability integral transformation (PIT) criterion for checking robustness of density forecasting (Diebold, 1998).

[9] For a mathematical representation of the Basel II approach, please see Vasicek (2002). Detailed derivation of this approach is presented in Bluhm, C., Overbeck, L. , and Wagner, C., (2003).

(ii) **Characterization of Loan Default Rate Distribution (explicit, closed form).** In order to model explicitly the default rate distribution, the Vasicek approach, uses a two step procedure.

a. **Characterization of Loan Defaults.** The default probabilities p_i, estimated for each type of loan in the previous step enters as a parameter in the Bernoulli distribution that characterizes the defaults of the obligors. From this parametric model, the characterization of defaults is obtained, since the Bernoulli density indicates if a given type of loan has defaulted or not.

b. **Approximation of Loan Default Rate Distribution.** Once loan defaults for each type of loan have been characterized, via a limit process (that is based on key assumptions, including that the number of obligors in a portfolio tends to infinity and that obligors are homogeneous), the default rate distribution of the portfolio is obtained. This is the Basel II default rate distribution. This density indicates (in the *x-axis*) the percentage of loans in the portfolio that falls into default and their likelihood of occurrence (y-axis).

(iii) **Computation of Loss Distribution.** For each type of loan, losses are computed by multiplying the unconditional default rate for each type of loan by their corresponding EAD and LGD. Losses for the portfolio are computed by adding up the losses across loan types.

Hence, once the probability of default PD for a loan is defined, it is possible to apply a closed form formula to define the capital requirement for the loan. This is highly convenient for its simplicity. Nevertheless, when applying this framework to estimate capital requirements for loan portfolios, key assumptions of the framework are usually violated, to a higher or lesser degree, including that the number of obligors in the portfolio tends to infinity and that obligors are uniformly correlated and admit a uniform unconditional probability of default.

Quantification of Losses under the CIMDO Approach

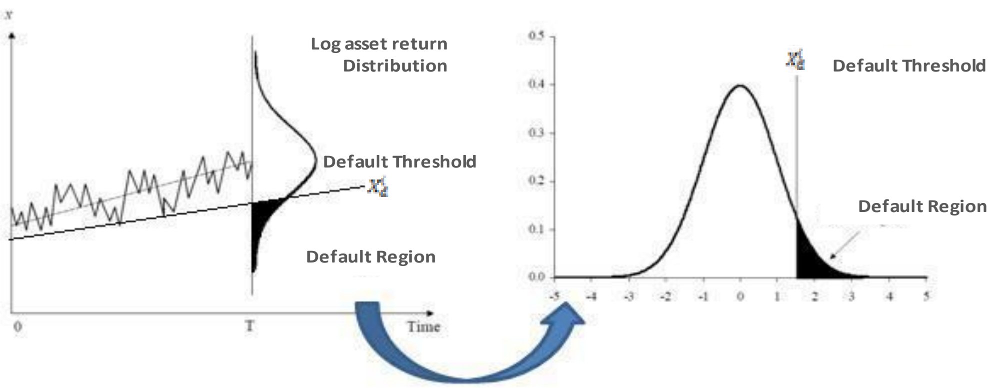
Contagion across financial institutions plays an important role in the realization of systemic risk. The global financial crisis of 2008–09 underlined that proper estimation of contagion risks among financial institutions (FIs) is essential for effective financial stability assessment. Clearly, the realization of simultaneous large losses in various FIs would affect a financial system's stability, and thus represents a major concern for authorities. Thus, the analysis of the financial system's stability should aim at identifying these contagion risks (due to direct and indirect linkages across FIs) and their changes across the economic cycle. [10]

[10] Direct linkages arise through inter-institution exposures (interbank deposits, lending, syndicated loans) and derivative transactions. However, indirect linkages can be due both to fire sale effects on asset values and to

(continued…)

For this purpose, we treat the financial system as a portfolio of FIs comprising the FIs operating in a country's financial system; henceforth, we apply the structural approach (SA) to estimate the systemic portfolio's risk, which embeds contagion risks across institutions.[11] The basic premise of the SA is that a borrowing firm's underlying asset value evolves stochastically over time and default is triggered by a drop in the firm's asset value below a threshold value (default region), the latter being modeled as a function of the firm's financial structure. Thus, the likelihood of the firm's asset value falling below the default-threshold is represented by the probability of default (PoD) of the firm (Figure 5).

Figure 5. Basic Premise of the Structural Approach



Source: Authors' calculation.

In line with the basic premise of the SA, the CIMDO approach allows us to estimate the financial system's portfolio multivariate density. This density describes the joint likelihood (due to direct and indirect linkages among FIs) of changes in the asset value of all the FIs that make up the financial system of a country (Figure 6). From the financial system's multivariate density (FSMD), it is possible to estimate: (i) the loss distribution of each financial institution in the system (via simulation) and from these, quantify each institutions' extreme losses (at the 99.9 percentile of the loss distribution),[12] and (ii) the marginal

(reputational) exposures to common risk factors, which are not usually apparent during calm periods, but can take greater relevance in periods of economic and financial distress.

[11] Note that the SA is normally used to measure risk in portfolios of loans. Widely known applications include the Credit Metrics framework (RiskMetrics Group, 2007). In contrast, in this exercise we apply the SA to measure risk in "portfolios of institutions," which characterize the financial system of a country.

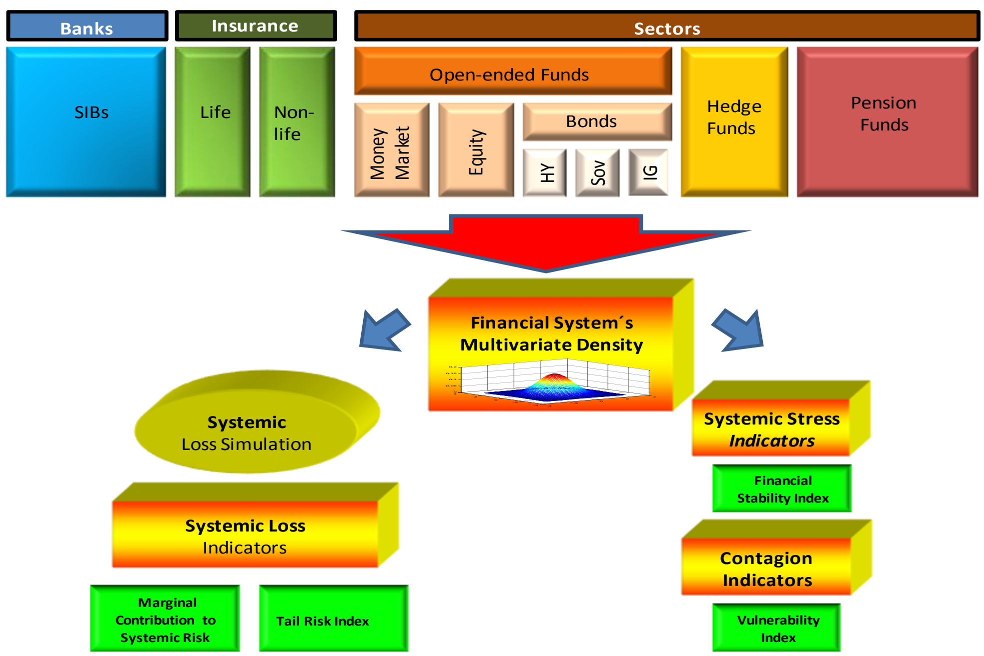
[12] From the financial system's multivariate density, we can also estimate a set of systemic financial stability measures (FSMs) and loss measures that characterize systemic risk by taking into account distress dependence between FIs and its changes across the economic cycle. As presented in Segoviano and Goodhart (2009), the FSMs allow for an analysis of financial stability from three different, yet, complementary perspectives, by allowing the quantification of: (i) "common" distress in the system, (ii) distress between specific FIs, and (iii) distress in the system associated with a specific FI; i.e., "cascade effects."

contribution to systemic risk that each institution brings to the system; i.e., the institutions' marginal contribution to systemic risk (MCSR).

From a statistical modeling perspective and an implementation standpoint, the CIMDO approach also offers significant advantages over alternative closed form or parametric approaches.

For example, the calibration of parametric approaches usually requires the availability of variables that indicate the evolution of FIs' underlying risk. However, policy makers in various jurisdictions might not have granular enough information to make adequate calibrations and might need to rely on highly aggregated data or some market-based variables to assess the probability of distress (PoDs) of individual FIs.[13]

Figure 6. Modeling Framework



Source: Authors' calculations.

Nevertheless, from the SA perspective, PoDs convey only partial information on the distribution that characterizes the implied log asset returns distribution of each FI in a financial system; equivalently, PoDs represent the likelihood that the FIs' implied log asset returns would fall in the default region (Figure 5). Nor, at the portfolio level, is it possible to observe the joint likelihood of changes in the risk quality of the various FIs that make up the

[13] Parametric versions of the SA characterized log asset return distributions using Gaussian processes; mixture of normals or other parametric elliptical distributions, including T-distributions.

financial system. As a result, when modelers try to specify portfolio multivariate distributions from the incomplete set of information provided by PoDs, they face an under-identified mathematical problem. When problems of under-identification arise, modelers can impose parametric assumptions to compensate for non-existing data. However, this course of action might produce distributions that are inconsistent with the analyzed assets' data-generating processes. This may lead to erroneous statistical inferences and incorrect economic interpretations (as already discussed in the case of the Vasicek model). Rather than imposing arbitrary distributional assumptions, the CIMDO approach is proposed as an alternative for the modeling of portfolio risk. The CIMDO density can be inferred from individual FIs' PoDs estimated with different approaches, including obviously the Merton approach employed in this paper (but also with PoDs estimated with other types of models), since PoDs are exogenous variables to the CIMDO approach. For these reasons, the CIMDO approach provides substantial flexibility in the estimation of a financial system's multivariate density.

The CIMDO-methodology is based on the minimum cross-entropy approach (Kullback, 1959). Under this approach, a *posterior* multivariate distribution *p*—the CIMDO-density—is recovered using an optimization procedure by which a *prior* density *q* is updated with empirical information via a set of constraints. Thus, the *posterior* density satisfies the constraints imposed on the *prior* density. In this case, the estimated PoDs of the banks represent the information used to formulate the constraint set. Accordingly the CIMDO-density is the *posterior* density that is closest to the *prior* distribution and that is *consistent* with the empirically estimated PoDs of the banks making up the system.

When we use CIMDO to solve for the CIMDO-density, the problem is converted from one of deductive mathematics to one of inference involving an optimization procedure. This is because, instead of assuming parametric probabilities to characterize information contained in the data, this approach uses the data information to infer values for the unknown probability density. Thus the recovered probability values can be interpreted as inverse probabilities. This procedure, seeks to make the best possible predictions when information is scarce. This feature of the methodology not only makes implementation simple and straightforward, it also seems to reduce model and parameter risks of the recovered distribution, as indicated by the PIT criterion (Segoviano, 2006). This is because, in order to recover the posterior density, only variables that are directly observable for the type of institutions that are the subject of interest (PoDs and stock prices in this case) are needed. Moreover, by construction, the recovered posterior density is consistent with the empirically observed probabilities of distress. Thus, the proposed methodology represents a more flexible approach to modeling multivariate densities, making use of the limited available information in a more efficient manner.

The CIMDO multivariate density embeds the dependence structure between the marginal densities that make up the multivariate density. This implies that when the economic situation worsens, the distress dependence structure between the marginals (which represent the log asset returns of each bank in the portfolio) increases. This is consistent with empirical facts. This is a key feature of the CIMDO approach, since dependence structure dynamically adjusts to changes in PoDs. Therefore, when PoDs increase, dependence increases. The estimation of loss distributions for FIs under the CIMDO approach can be summarized in the following five steps:[14]

i) **Characterization of the log asset return distribution.** The distribution that characterizes the log asset returns of the portfolio of FIs making up a financial system is characterized by the CIMDO multivariate density.

ii) **Simulation of log asset returns.** Using a Monte-Carlo simulation approach, which employs as its data generating process, the log asset return distribution defined in the previous step, simulations of log asset returns for each FI x_n (of a portfolio containing *n* FIs; i.e., x_1, $x_{2,}$ x_3, …, x_n characterize (simulated) log asset returns of FIs 1, 2, 3, …, n) are simulated *m* times.

iii) **Characterization of defaults and risk deterioration (Indirectly).** From the simulated log asset returns in the previous step, it is possible to characterize FIs that fall in distress. These are FIs whose simulated log asset returns fall in the "default region". Since under the SA, the value of a company's log asset return determines the company's ability to pay its debt, FIs are considered as "defaulted", if (simulated) values of their log asset returns fall in the region where log asset returns are lower than the default threshold (Figure 5). Therefore, quantification of default is done indirectly via simulation of log asset returns. This procedure is repeated for *m* simulations for each FI. This procedure is also extendable to take account not only of default but also of FIs' risk deterioration. See Appendix II.

iv) **Estimation of loss distributions for individual institutions.** For each FI, the computation of its distribution of potential losses is done by adding up the losses implied by log asset returns that fell in the "default region" plus the losses implied by log asset returns that represented a deterioration of risk quality in each of the *m* simulations. Once a quantification of losses has been done for each of the *m* simulated log asset returns, a histogram is made with the *m* simulated losses. This histogram characterizes the portfolio loss distribution (PLD) for each FI in the system. Losses incurred by random draws of log asset returns that fall in the "default region" are quantified by mapping a loss rate of 100 percent to the random draw and multiplying the loss rate by the FI asset value; i.e., "exposure at default" (EAD) and

[14] See Appendix II for a summary of the approach to estimate loss distributions using the CIMDO approach. Mathematical details of the CIMDO density are presented in Segoviano (2006).

by a “loss given default” (LGD) of 45 percent[15]. Losses incurred by random draws that implied risk deterioration (but not default), are quantified estimated by mapping the random draw to a loss rate (smaller than 100 percent) and multiplying the loss rate by the FIs’ EAD and by a 45 percent LGD.

v) **Estimation of the marginal contribution to systemic risk.** Our analysis aims at estimating the potential extreme losses that the system can have taking into account the direct and indirect linkages (interconnectedness) that exist between the institutions that make up the system and the relative size of each institution in the system (size). Hence, systemic losses can be large if an institution that is highly interconnected or is relatively large (or an institution with a combination of high interconnectedness and large size) suffers large losses. Direct linkages arise through inter-institution exposures (interbank deposits, lending, syndicated loans) and derivative transactions. However, indirect linkages can be due to exposures to common risk factors, which are not usually apparent during calm periods, but can take greater relevance in periods of economic and financial distress. The CIMDO multivariate describes the joint likelihood of changes in the asset value of <u>all</u> the FIs that make up the portfolio that characterize the financial system; hence, the systemic losses estimated from this density (via simulation) take into account the interconnectedness between the FIs that make up the financial system and the institutions’ size. The systemic loss simulation allows estimating the marginal contribution to systemic risk (MCSR) of each FI in the system (see Appendix III).

Empirical Results

To illustrate how to use the methods we propose to obtain an empirically usable framework for setting an intervention point for recovery, we use data from the following banks:

Sample of Banks

- Germany: Deutsche Bank, Commerzbank.
- France: Credit Agricole, BNP Paribas, Societe Generale.
- United Kingdom: HSBC, Barclays, Lloyds, Standard Chartered.
- Spain: Banco Bilbao Vizcaya, Santander, Popular Espanol, Sabadell, Bankinter.
- Italy: Intesa San Paolo, Unicredit, Banca Monte dei Paschi Siena.

[15] The LGD of 45 percent has been adopted by credit risk modelers worldwide as a reasonable assumption for loss estimation in the absence of data to estimate LGDs.

- Failed Banks: Washington Mutual (WaMu) , Royal Bank of Scotland (RBS), HBOS, Lehman Brothers.

Input Variables

For each of the banks, we obtained or estimated the following variables from January 1, 2007 (or the first date when data was available) to December 31, 2012.

Daily Frequency: CDS spreads, stock prices, log stock returns, market capitalization, index of global risk aversion.

Quarterly Frequency: total equity, tier 1 equity, regulatory capital, total assets, total liabilities, long term liabilities, short term liabilities, provisions, total equity to total assets ratio, tier 1 to total assets ratio, risk sensitive loss absorption buffer = [Provisions + Market capitalization]/Total assets, [Provisions + Regulatory capital]/Total assets.

Probabilities of Distress: We used two alternative approaches, CDS PoDs and Merton PoDs.

CDS PoD. Based on the no-arbitrage theorem, CDS spreads can be used to extract PoDs. Unfortunately, these data only existed for most banks for the period 2008-2009. Moreover, results showed inconsistencies in some cases. Therefore, we decided not to use this variable.

Merton PoD. The Merton model produces PoDs as functions of equity volatility, equity returns and liability thresholds. We proceeded to estimate daily values of the Merton PoDs using daily equity volatility and the beginning of quarter liability threshold. These parameters were calibrated as follows:

> ***The liability threshold.*** The alternatives that were explored included defining the thresholds as equal to: (i) short term liabilities, (ii) short term liabilities plus 50 percent of long term liabilities (ST+50LT), (iii) total liabilities (short term plus long term liabilities) and (iv) fifty percent of total liabilities. We got the most consistent results when we used (ii).
>
> ***Volatility value.*** Volatility can be estimated with historical values at different windows or using option prices to extract implied volatilities. For historical volatilities, we used 180 and 360 days. We also estimated implied volatilities from option prices. We followed the latter option, since it produced the most consistent results.

Quantification of Losses

As discussed above, for each bank we estimated losses following the Vasicek approach and the threshold (CIMDO) approach. Table 1 shows results for the insolvent banks. These include the banks' PoDs, distance to default (DD)[16], losses at the 99. 9 percentile (under the "Threshold Model" and "Vasicek Model") and banks' buffers (Provisions + Market Cap)/TA.[17] This table also indicates (in yellow) the periods when banks' extreme losses (under both approaches) became larger than their buffers. For example, for Washington Mutual, losses under the "Threshold Model" were larger than buffers from March 2008, while losses under the "Vasicek Model" were larger than buffers from December 2007.

[16] DD is a transformation of the PoD defined as DD=-NORMSINV(PoD), where NORMSINV is the inverse of the standard normal cumulative distribution.

[17] Losses and buffers are expressed as percentage of banks' assets.

Table 1. Bank Unexpected Losses and Loss Absorption Buffers

Date	Washington Mutual PoD	DD	Threshold Model Percentage Loss	Vasicek Model Percentage Loss	(Provisions + Market Cap)/TA Percentage
2007M03	0.01 percent	3.68	0.05 percent	0.29 percent	**11.70 percent**
2007M06	0.01 percent	4.26	0.00 percent	0.04 percent	**12.63 percent**
2007M09	0.47 percent	2.60	0.09 percent	4.26 percent	**9.88 percent**
2007M12	9.86 percent	1.29	3.98 percent	18.42 percent	**4.39 percent**
2008M03	14.62 percent	1.05	8.71 percent	22.84 percent	**4.32 percent**
2008M06	19.37 percent	0.86	13.50 percent	26.42 percent	**4.42 percent**
2008M09	33.79 percent	0.42	15.92 percent	34.05 percent	**4.42 percent**
Date	**Royal Bank of Scotland PoD**	**DD**	**Threshold Model Percentage Loss**	**Vasicek Model Percentage Loss**	**(Provisions + Market Cap)/TA Percentage**
2007M03	0.00 percent	4.26	3.97 percent	0.04 percent	**6.59 percent**
2007M06	0.00 percent	4.26	4.01 percent	0.04 percent	**6.34 percent**
2007M09	0.11 percent	3.06	4.08 percent	1.66 percent	**5.32 percent**
2007M12	0.90 percent	2.37	4.45 percent	6.00 percent	**2.76 percent**
2008M03	6.85 percent	1.49	6.83 percent	15.07 percent	**2.18 percent**
2008M06	9.66 percent	1.30	8.30 percent	18.21 percent	**2.11 percent**
2008M09	8.38 percent	1.38	7.48 percent	16.83 percent	**1.84 percent**
2008M12	12.96 percent	1.13	9.32 percent	21.41 percent	**1.26 percent**

Date	HBOS PoD	DD	Threshold Model Percentage Loss	Vasicek Model Percentage Loss	(Provisions + Market Cap)/TA Percentage
2007M03	0.01 percent	3.78	0.81 percent	0.21 percent	**6.54 percent**
2007M06	0.01 percent	3.85	0.82 percent	0.16 percent	**6.44 percent**
2007M09	1.03 percent	2.32	1.18 percent	6.39 percent	**6.49 percent**
2007M12	1.28 percent	2.23	1.28 percent	7.08 percent	**4.62 percent**
2008M03	8.28 percent	1.39	3.47 percent	16.71 percent	**3.61 percent**
2008M06	20.47 percent	0.82	7.67 percent	27.15 percent	**2.62 percent**
2008M09	12.54 percent	1.15	4.70 percent	21.03 percent	**2.33 percent**
Date	**Lehman Brothers PoD**	**DD**	**Threshold Model Percentage Loss**	**Vasicek Model Percentage Loss**	**(Provisions + Market Cap)/TA Percentage**
2007M03	0.00 percent	4.14	0.03 percent	0.06 percent	**4.55 percent**
2007M06	0.00 percent	4.26	0.00 percent	0.04 percent	**5.10 percent**
2007M09	0.18 percent	2.91	0.14 percent	2.32 percent	**4.30 percent**
2007M12	2.20 percent	2.01	0.33 percent	8.90 percent	**3.34 percent**
2008M03	11.02 percent	1.23	9.45 percent	19.59 percent	**3.93 percent**
2008M06	8.25 percent	1.39	4.23 percent	16.67 percent	**3.83 percent**
2008M09	20.77 percent	0.81	41.99 percent	27.34 percent	**3.13 percent**

Source: Authors' calculations

D. Choice of Intervention Thresholds

In Section II, we argued that an institution should become subject to supervisory intervention only when its potential extreme losses became equal or larger than its loss absorption buffer. However the degree of intervention, which we propose to make increasingly punitive, should increase progressively as an institution's value of capital (defined as the Loss Absorption Buffer) declines and its probability of distress (PoD) and associated potential losses increase. Thus, we suggest the following sanctions (starting from the least severe):

1. **Frequent visit sanction.** Obligation of banks' management to meet with supervisory authorities more frequently;

2. **Pecuniary charge sanction.** Regulators start levying an increasing pecuniary charge on the institution;

3. **Remuneration sanction.** Limitations on the bank's ability to payout dividends or bonus remuneration;

4. **Intervention.** Intervention action might imply a bail out or bail in of creditors, as discussed below.

So, how do we define the sanction-associated thresholds to activate the different degrees of intervention? The definition of intervention thresholds is a subjective exercise because thresholds depend on policy makers' objectives and risk aversion. However, we suggest that it would be preferable to make those decisions based on statistical evidence. To provide that evidence, we took the following steps:

1. **Histogram of potential losses exceeding LoA Buffers for solvent and insolvent banks**. We calculated the losses and LoA Buffers for 19 large banks (15 that remained solvent and 4 that became insolvent) between January 2007 and December 2012. Then, based on the criterion for intervention defined earlier, we identified the periods in which potential losses were equal or larger than LoA Buffers for the sample of banks under analysis under the threshold and Vasicek loss estimation approaches (Table 1). With this information we constructed two histograms (for each loss estimation approach), which characterize the frequency of solvent and insolvent banks (whose potential losses exceeded their LoA Buffers) and relate those frequencies to the levels of PoD (or their transformation to Distance to Default (DD)) of the banks.

2. **Estimation of cumulative frequency functions for solvent and insolvent banks.** With the Histograms described above, we constructed cumulative frequency functions (CF) for the solvent and insolvent banks, under both loss estimation approaches (Figures 7a and 7b). These functions characterize the cumulative frequency of banks (on the *y-axis*), whose potential losses exceeded their LoA Buffers, up to an observed

level of PoD, or their transformation to DD (n the *x-axis*). These functions provide a useful tool to define the intervention thresholds as discussed below.

Figure 7a. Losses Above Loss Absorption Buffer. Threshold Approach
(in Cumulative Frequency)

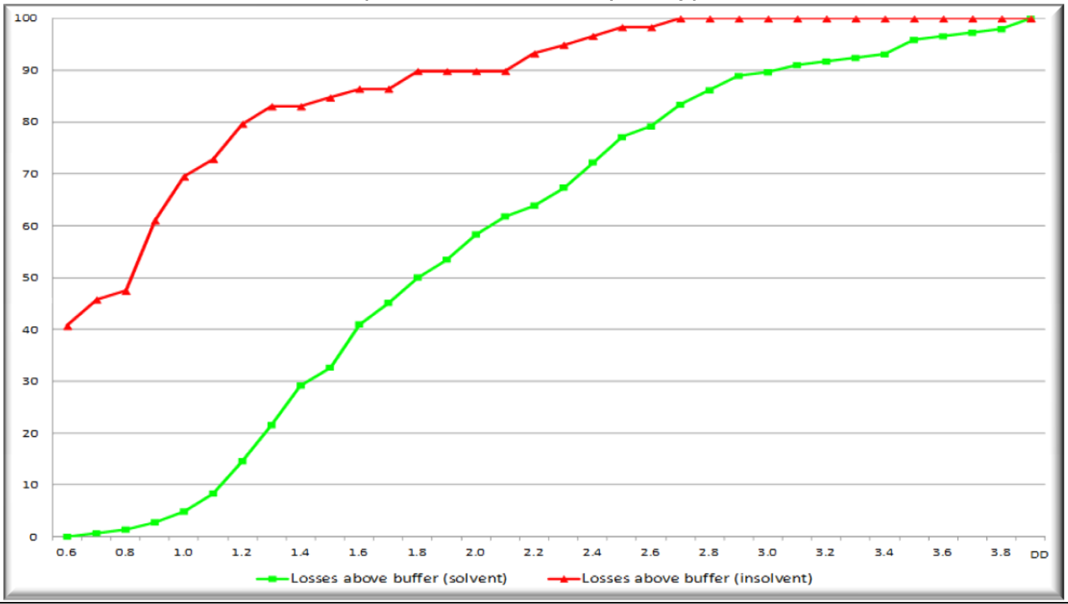
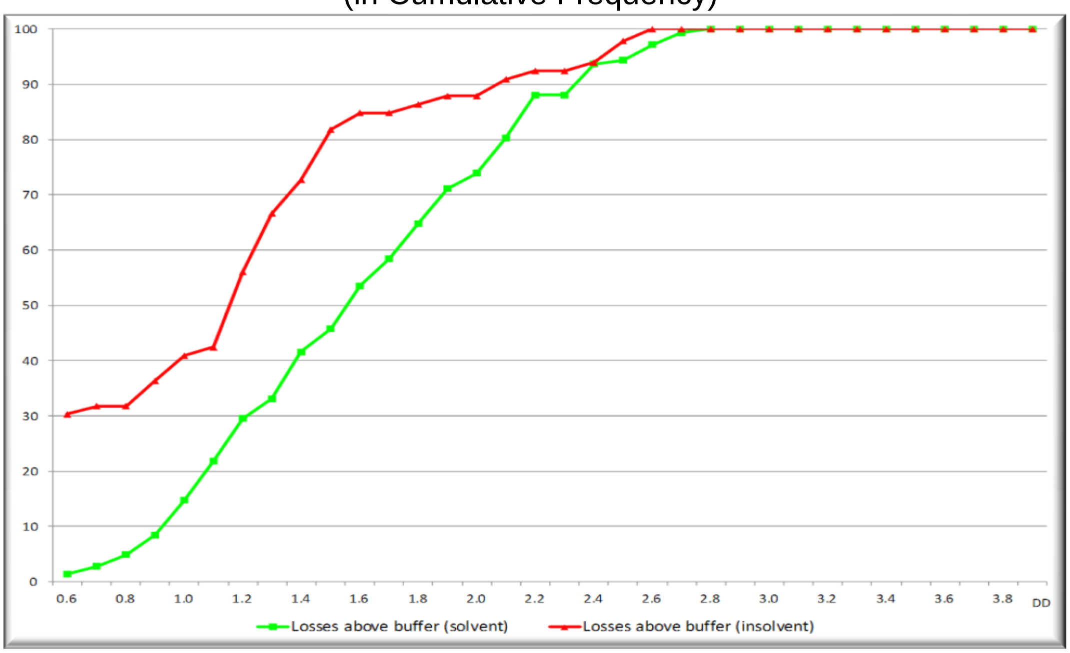


Figure 7b. Losses Above Loss Absorption Buffer. Vasicek Approach
(in Cumulative Frequency)



Source: Authors' calculations.

Note*: the x-axis* shows the DD, which is a transformation of banks' PoD. DD= - NORMSINV(PoD), where NORMSINV is the inverse of the standar*d nor*mal cumulative distribution. The *y-axis* shows the cumulative frequency of banks (in the *y-axis*), whose potential losses exceeded their LoABuffers

E. Identification of Intervention Thresholds

Recovery Trigger. A principle that we propose to follow is to set the most severe trigger; i.e., the recovery trigger, at a point that minimizes the combination of type I errors (not intervening to close down the operation of a bank which subsequently would fail) and type II errors (closing a bank which would survive on its own). As mentioned earlier, the balance between these two errors would depend on the authorities' objectives and risk aversion. While externalities arising from bank failures would suggest placing more weight on minimizing type I errors, the expropriation of existing ownership rights in a market based economy is sufficiently draconian and often legally complex to suggest also placing considerable weight on avoiding type II errors. Based on our proposed principle, and assisted by the cumulative frequency (CF) presented in Figures 7a, 7b, we propose an intervention threshold at DD= 1.50 (PoD= 6.68).[18]

The CF of the insolvent banks displayed in Figures 7a, 7b show that this threshold implies that 85 percent of the banks that became insolvent, after their potential losses exceeded their LoABuffer, had a DD equal to, or smaller than, 1.50 (PoD equal to or larger than 6.68). Hence, of all the banks that became insolvent, 15 percent would have not been intervened at this threshold. Equivalently, for this sample, this threshold implies a type I error of 15 percent. By examining the CF of solvent banks, we also see that 33 percent of banks that remained solvent (after their potential losses exceeded their LoA) would have been intervened unnecessarily at this threshold; hence, this threshold implies a type II error of 33 percent. Empirical observations in our sample indicate that when banks reached PoDs of above 6-7 percent, banks' equity had lost on average 70–80 percent of their value (vs. the non-stressed period in 2007).[19]

Our choice of threshold is trying to strike a balance between type I and type II errors. If we moved the threshold to the right (on the *x-axis* of the CF chart), we would lower type I errors at the expense of increasing type II errors. Ultimately, based on this framework, authorities of a particular country could calibrate the thresholds to target a combination of errors based on their own preferences.

Limits on Pay Threshold. After defining the recovery (most severe) threshold, we proceed to define the less severe intervention thresholds. Concretely, the limits on pay threshold; i.e., the

[18] Remember that we do not advocate making the precise numbers publicly observable, only the principle of the approach should be made public. Each bank; however, should be told exactly how it would be treated under the different intervention thresholds.

[19] Results using the Vasicek loss estimation threshold (Figure 7b) show that 82 percent of the banks that later became insolvent (after their potential losses exceeded their LoA Buffer) had a DD equal to or smaller than 1.50 (PoD equal to or larger than 6.68). Hence, of all the banks that became insolvent, 18 percent would have not been intervened at this threshold (type I error). By examining the CF of solvent banks, we also see that 46 percent of banks that remained solvent (after their potential losses exceeded their LoA Buffer) would have been intervened unnecessarily at this threshold (type II error).

threshold at which banks would face limitations on their ability to payout dividends or bonus remuneration, was defined at a DD=1.9 (PoD=2.87). By examining the CF of the insolvent banks (Figure 7a), we see that this threshold implies that 90 percent of the banks that later became insolvent (after their potential losses exceeded their LoABuffer) had a DD equal to or smaller than 1.9 (PoD equal to or larger than 2.87). Hence, of all the banks that became insolvent, 10 percent would have not been restricted to pay out dividends or bonus remuneration (type I error of 10 percent). Similarly, by examining the CF of solvent banks, we see that 53 percent of banks that remained solvent (after their potential losses exceeded their LoA) would have been restricted from paying dividends or bonus remuneration unnecessarily at this threshold; hence, this threshold implies a type II error of 53 percent. Although minimizing type I and type II errors is still important in this case, it is not as important as in the case of the "intervention threshold". Moreover, empirical observations in our sample indicate that when banks reached PoDs of above 2–3 percent, banks' equity had lost on average about 40–50 percent of their equity value (vs. the non-stressed period in 2007).[20]

Fines Threshold. This threshold was defined at DD=2.3 (PoD=1.07). The CF of insolvent banks shows that 95 percent of insolvent banks had a DD equal to or smaller than 2.3 (PoD equal to or larger than 1.07) Hence, a type I error of 5 percent. The CF of solvent banks indicate that 67 percent of solvent banks would have a DD equal to or smaller than 2.3 (PoD equal to or larger than of 1.07); i.e., type II error of 67 percent. Nevertheless, the benefits of imposing this sanction on insolvent banks is likely to outweigh the cost of incurring in type II error in solvent banks.[21]

Frequent Oversight Threshold. This threshold was set at DD= 2.5 (PoD=.62). The CF indicates that 98 percent of insolvent banks and 77 of solvent banks have a DD of 2.5 or lower. This threshold implies a type I error of 2 percent and a type II error of 77 percent. Even if type II error is large, the benefits of imposing this sanction on insolvent banks might outweigh the cost of incurring in type II error in solvent banks. Additionally, although the PoD implied by this threshold is relatively low, the imposition of more frequent visits sanctions might be appealing to "risk averse" supervisors who would be interested in following more closely banks whose potential losses have exceeded their LoABuffers in certain periods. Note that

[20] Results using the Vasicek loss estimation threshold (Figure 7b) show that 88 percent of the banks that later became insolvent (after their potential losses exceeded their LoA Buffer) had a DD equal to or smaller than 1.9. Hence, of all the banks that became insolvent, 12 percent would have not been intervened at this threshold (type I error). We also see that 71 percent of banks that remained solvent (after their potential losses exceeded their LoA Buffer) would have been intervened unnecessarily at this threshold (type II error).

[21] Results using the Vasicek loss estimation threshold (Figure 7b) show that 92 percent of the banks that later became insolvent had a DD equal to or smaller than 2.3. Hence, of all the banks that became insolvent, 8 percent would have not been intervened at this threshold (type I error). We also see that 88 percent of banks that remained solvent would have been intervened unnecessarily at this threshold (type II error).

although the threshold is high (in DD terms), there is still a relatively good differentiation between solvent and insolvent banks.[22]

Table 2 summarizes the discussion in this section. It shows cumulative frequencies of losses above LoA Buffers for solvent and insolvent banks and the implied type I and type II errors under the Threshold and Vasicek loss estimation frameworks.

Table 2. Type I and Type II errors under the Threshold and Vasicek Framework

Intervention Action			Threshold Model				Vasicek Model			
DD	PoD	Threshold	Losses above buffer (insolvent) Percent	Losses above buffer (solvent) Percent	Type I Percent	Type II Percent	Losses above buffer (insolvent) Percent	Losses above buffer (solvent) Percent	Type I Percent	Type II Percent
1.50	6.68	Recovery	85	33	15	33	82	46	18	46
1.90	2.87	Limits on Payouts	90	53	10	53	88	71	12	71
2.30	1.07	Fines	95	67	5	67	92	88	8	88
2.5	0.62	Frequent Oversight	98	77	2	77	97	94	3	94

Source: Authors' calculations

F. Lag between Recovery Intervention and Insolvency Announcement

Based on our sample and calculations, we identified for each bank in the sample the date when the DD was equal or lower than 1.50 (the PoD equal or higher than 6.68). According to our proposal, this would have been the date when the authorities would have triggered intervention for recovery (Table 1). We then compared those date with the actual date when the bank was intervened and declared insolvent. We see that, if our approach had been in place, intervention would have taken place between six to eight months before the insolvency announcement (Table 3). Triggering the recovery phase should happen before the bank is required to fall into resolution in order to give remedial measures a chance to take effect successfully. The results in Table 3 thus suggest that the CIMDO approach would provide such a valuable early warning mechanism.

G. Marginal Contribution to Systemic Risk

The systemic importance of an institution is based on the potential losses that such institution could cause to the system if it falls into distress. Distress of an institution can cause distress in the system if the institution is large, if it is highly interconnected with other institutions in the system or if it is relatively large. The marginal contribution (of an institution) to systemic risk can be appropriately quantified by the Shapley value, which divides the risk of the system into N parts corresponding to each institution in the system; i.e., the sum of all

[22] Under the Vasicek framework, The CF indicates that 97 percent of insolvent banks and 94 of solvent banks have a DD of 2.5 or lower. This threshold implies a type I error of 3 percent and a type II error of 94 percent.

marginal contributions to systemic risk (MCSR) is equal to 100 percent. The share allocated to each institution is based on the losses that the institution could cause to the system, which in turn are determined by the institution's relative size and interconnectedness with the system.

Table 3. Recovery Intervention Time Window

IV. Institution	Actual Intervention	Recovery Trigger	Threshold PoD>6.68		Time Period
	Date	Date	DD	PoD	Months
Washington Mutual	September 25, 2008	Dec-07	1.29	9.86	8
Royal Bank of Scotland	October 7, 2008	Mar-08	1.49	6.85	6
HBOS	September 18, 2008	Mar-08	1.39	8.28	6
Lehman Brothers	September 15, 2008	Mar-08	1.23	11.02	6

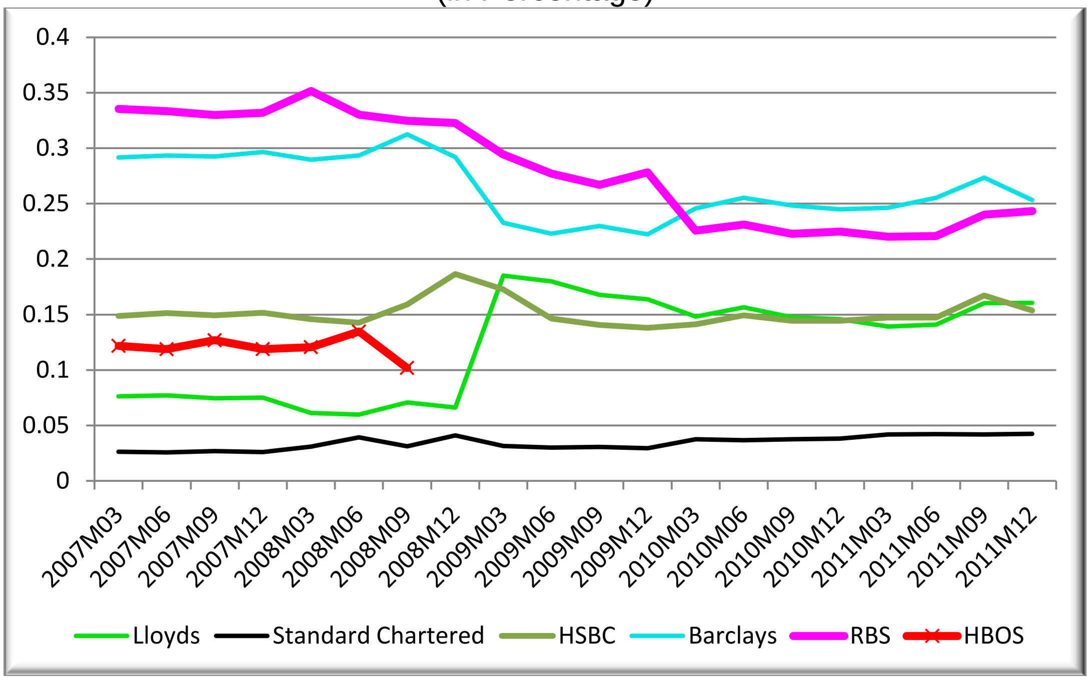
Source: Authors' calculations

The estimated MCSR of the British institutions in the sample using the potential losses estimated using the threshold approach (including the failed banks RBS and HBOS) are presented in Figure 8. The estimated MCSR suggests that RBS and Barclays were the most systemically important banks in the U.K since 2007, whereas Standard Chartered was the least systemic. Note however, that the ranking of systemic importance has changed after 2009.

While the relative size of a bank is an important determinant of the losses that can cause in the system, increases of the interconnectedness of the institution with the system, especially when the institution is under distress, also can have significant impact on systemic risk. In order to explore this, we computed the ratio of the MCSR to the relative size of the institution. If the MCSR is driven purely by size, this indicator should be very close to 1. However, if the losses provoked in the system by the institution are larger than their relative size, the ratio should be greater than 1; e.g., the institution "adds" risk to the system. Conversely, if losses induced in the system by the institution are smaller than the institution's relative size, the ratio should be less than 1; e.g., the institution "diversifies" risk from the system. Table 4 indicates that on average, Standard Chartered and HSBC have diversified risk from the U.K. banking system.

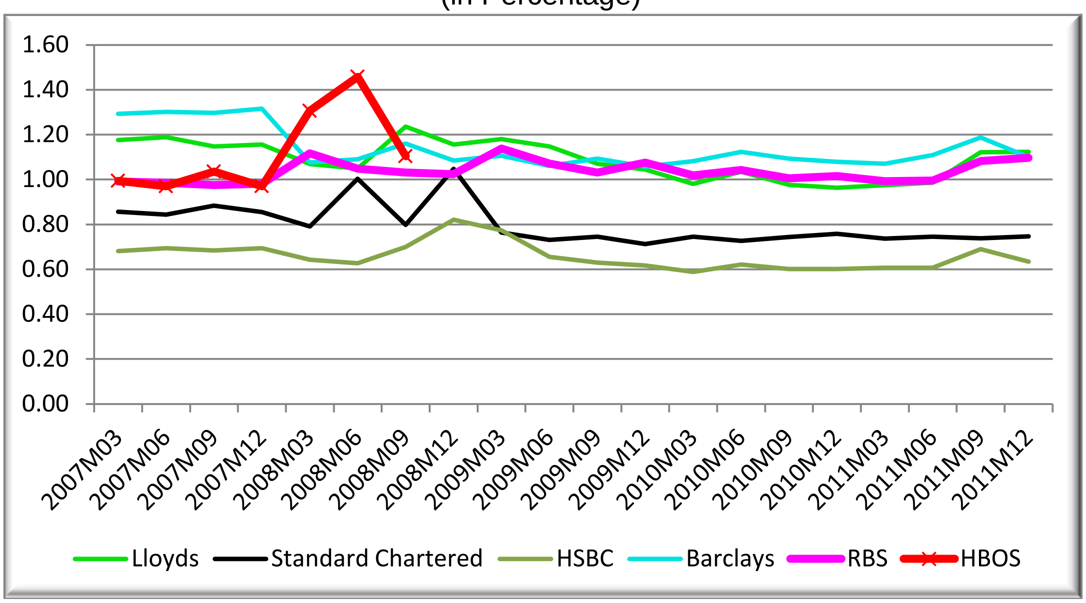
Figure 9 also shows that during the last half of 2008, RBS and HBOS exhibited the largest ratios of MCSR/size, suggesting that these institutions added the highest level of risk to the U.K. banking system. Note that RBS ratio reached its peak on March 2008 (seven months before its failure), while HBOS ratio reached its peak on June 2008, three months before its failure date. Hence, the MACSR/size ratio consistently indicated that the institutions that subsequently failed were the institutions that contributed most significantly to systemic risk before the institutions' failure.

Figure 8. Marginal Contribution to Systemic Risk. U.K. Banking System (in Percentage)



Source: Authors' calculations

Figure 9. Marginal Contribution to Systemic Risk/Size Ratio. U.K. Banking System (in Percentage)



Source: Authors' calculations

Table 4. Marginal Contribution to Systemic Risk/Size Ratio. U.K. Banking System

Date	Lloyds	Standard Chartered	HSBC	Barclays	RBS	HBOS
2007M03	1.18	0.86	0.68	1.29	0.99	0.99
2007M06	1.19	0.84	0.69	1.30	0.99	0.97
2007M09	1.15	0.88	0.68	1.30	0.98	1.04
2007M12	1.16	0.85	0.69	1.32	0.98	0.97
2008M03	1.07	0.79	0.64	1.08	1.12	1.31
2008M06	1.05	1.00	0.63	1.09	1.05	1.46
2008M09	1.24	0.80	0.70	1.16	1.03	1.10
2008M12	1.16	1.05	0.82	1.08	1.02	
2009M03	1.18	0.76	0.77	1.11	1.14	
2009M06	1.15	0.73	0.66	1.06	1.07	
2009M09	1.07	0.75	0.63	1.09	1.03	
2009M12	1.04	0.71	0.62	1.06	1.08	
2010M03	0.98	0.75	0.59	1.08	1.02	
2010M06	1.03	0.73	0.62	1.12	1.04	
2010M09	0.98	0.74	0.60	1.09	1.01	
2010M12	0.96	0.76	0.60	1.08	1.01	
2011M03	0.98	0.74	0.61	1.07	0.99	
2011M06	0.99	0.74	0.61	1.11	1.00	
2011M09	1.12	0.74	0.69	1.19	1.08	
2011M12	1.12	0.75	0.63	1.10	1.10	
Average	1.09	0.80	0.66	1.14	1.04	1.12

Source: Authors' calculations

IV. Summary and Conclusions

Mitigation of systemic risk in a financial system would be improved if intervention to stop a failing bank could be initiated earlier. Although all systemically important intermediaries are now required to develop recovery and resolution plans, ('Living Wills'), we think it highly improbable that banks will trigger their own recovery phase until bankruptcy is staring them in the face. Therefore, there is a need for an objective metric which would help supervisory and regulatory authorities trigger the onset of the recovery phase for a bank earlier. In this paper we have developed a framework that can be used to estimate such metric. This "intervention metric" is based on the relationship between loss absorbing buffers and potential extreme losses. Importantly, the proposed framework to estimate the intervention metric can be implemented with the use of alternative quantitative approaches to estimate potential losses; hence, the proposed framework offers authorities great flexibility to quantify the intervention metric.

In order to illustrate how to implement the proposed framework, we used the Vasicek model and Threshold-approach to estimate bank losses. The Vasicek approach was chosen mainly due to its theoretical simplicity; however, its use carries the cost of breaking key assumptions of the model and hence, a high risk of lack of robustness and inconsistency of empirical results. The Threshold-approach was chosen due to two main features. First, approach the possibility to account for systemic risk; i.e., the contagion that any given bank can generate on other banks in the system (which we consider a key advantage when assessing financial stability). Second, this is a non parametric model; hence, it is based on fewer assumptions; so, it is a more robust model in the presence of restricted data, which most authorities would likely face when implementing the framework.[23] However, the Threshold-approach embeds a more complex theoretical framework and elaborate estimation, since it requires a simulation exercise to calculate losses. Nevertheless, once PoDs are estimated, both approaches are relatively easy to implement. We have also presented empirical results for such an exercise. Table 3, clearly shows that errors type I and type II are larger under the Vasicek approach. This is not surprising, given that in this application, key assumptions of the model break down.

Hence, in order to choose an approach for the estimation of losses, authorities would have to evaluate how comfortable they might feel with the theoretical approaches and also evaluate the type and quality of data available and the theoretical assumptions of the model that may not hold in reality. The framework that we propose used define intervention thresholds can be implemented irrespective of the approach to estimate PoDs and losses.
Moreover, the proposed framework has the advantage that it could be broadened to encompass a whole ladder of sanctions which get progressively tougher as the ratio of buffer to potential extreme losses narrows.

[23] Under the probability integral transformation (PIT) criterion for checking robustness of density forecasting (Diebold, 1998).

Appendix I. The Vasicek Approach

1. **Characterization of log asset return distribution.** Following the basic premise if the structural approach, the log asset returns are represented by the following expression: $r_i = \sqrt{\varrho}Y + \sqrt{1-\varrho}Z_i$, where Y refers to a single macroeconomic factor, Z_i represents the specified effect or idiosyncratic component of obligor i and ϱ denotes the uniform asset correlation assumed in the model. We assume $Y, Z_1, \ldots, Z_m$ to be i.i.d. standard normal random variables (we are also assuming that there are m obligors in the portfolio with a unconditional uniform PD). Conditioning on the state of the economy Y a uniform (conditional) probability of default is obtained for each obligor.

2. **Characterization of Loan Default Rate Distribution.**

   a. **Characterization of Loan Defaults.** The link between the Bernoulli variables L_i indicating default or survival and the asset return decomposition at the horizon comes from the threshold definition of default of the structural approach:

$$L_i = 1_{\{r_i < c\}} = \begin{cases} 1 \; if \; r_i < c, \\ 0 \; otherwise. \end{cases}$$

   where c denotes the uniform default threshold of all obligors.
   Given the conditional default probability for each obligor $p(y)$, the default rate distribution L can be calculated as:

$$L = \frac{\sum_{i=1}^{m} L_i}{m}.$$

   b. **Approximation of Loan Default Rate.** It is a long known insight that if one increases the number of obligor's m in a homogeneous portfolio with a uniform default probability PD and a uniform asset correlation ϱ, then the distribution of the portfolio loss converges to a limit distribution with $P[L \leq x] = P[p(y) \leq x] = N\left[\frac{1}{\sqrt{\rho}}\left(N^{-1}[x]\sqrt{1-\rho} - N^{-1}[PD]\right)\right]$, where $L = p(y)$ denotes the percentage portfolio loss of the limit portfolio admitting infinitely many obligors that are uniformly correlated and admit a uniform unconditional probability of default PD.

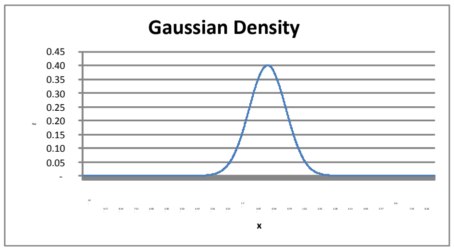
Computation of Loss Distribution. Under the Basel II framework the regulatory capital for each type of loan is given by multiplying the EAD and LGD by the 99.9 percent percentile of L minus the uniform PD, which is a correction for expected losses. [24]

[24] For a detailed derivation see Bluhm, C., Overbeck, L. , and Wagner, C., (2003) or Ong, M., (2007).

ESTIMATION OF THE LOSS DISTRIBUTION OF A PORTFOLIO OF LOANS UNDER THE BASEL II APPROACH

2. Characterization of Loan Default Rate Distribution (explicit, closed form).

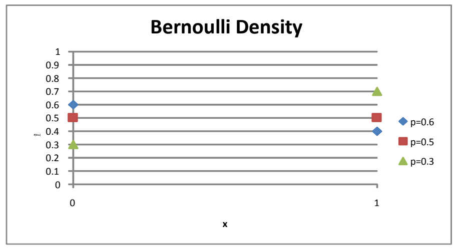
1. Characterization of state of economy/ log asset return.



The log asset return of a firm is assumed to depend on a factor that reflects the state of the economy and an idiosyncratic component. Thus, implied log asset returns and the probability of default p_i for each type of loan *i*, are conditional on the state of the economy.

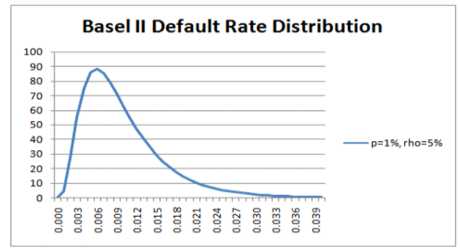
This distribution is defined in the interval $(-\infty,\infty)$

2a. Characterization of Loan Defaults.



This distribution is defined in the set $\{0,1\}$

2b. Approximation of Loan Default Rate Distribution.

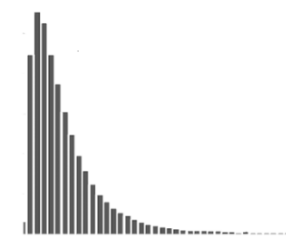


This distribution is defined in the interval $[0,1]$

2a. The default probabilities p_i, estimated for each type of loan in the previous step enters as a parameter in the Bernoulli random variables that model the defaults of the obligors. From this parametric model, characterization of defaults is done, since the Bernoulli density indicates whereas a given type of loan has defaulted or not.

2b. Once loan defaults for each type of loan have been characterized, via a limit process (that assumes that the number of obligors in a portfolio tends to infinity among others), the default rate distribution of the portfolio is obtained. This is the Basel II default rate distribution. This density indicates (in the *x-axis*) the percentage of loans in the portfolio that falls in default and their likelihood of occurrence (y-axis).

3. Computation of Loss Distribution.



For each type of loan, losses are computed by multiplying the unconditional default rate for each type of loan by their corresponding EAD and LGD. Losses for the portfolio are computed by adding up the losses across loan types.

Appendix II. The CIMDO-Approach

In order to formalize the CIMDO approach, Segoviano and Goodhart (2009) proceed by defining a banking system—portfolio of banks—comprising two banks;[25] i.e., bank X and bank Y, whose logarithmic returns are characterized by the random variables x and y. Hence we define the CIMDO-objective function as:

$$C[p,q]=\int\int p(x,y)\ln\left[\frac{p(x,y)}{q(x,y)}\right]dxdy, \text{ where } q(x,y) \text{ and } p(x,y)\in \mathbf{R}^2 .$$

The *prior* distribution follows a parametric form q that is consistent with economic intuition (e.g.,, default is triggered by a drop in the firm's asset value below a threshold value) and with theoretical models (i.e., the structural approach to model risk). However, the parametric density q is usually inconsistent with the empirically observed measures of distress. Hence, the information provided by the empirical measures of distress of each bank in the system is of prime importance for the recovery of the *posterior* distribution. In order to incorporate this information into the *posterior* density, we formulate consistency-constraint equations that have to be fulfilled when optimizing the CIMDO-objective function. These constraints are imposed on the marginal densities of the multivariate *posterior* density, and are of the form:

$$\int\int p(x,y)\,\chi_{\left(x_d^x,\infty\right)}dxdy=PoD_t^x, \int\int p(x,y)\,\chi_{\left(x_d^y,\infty\right)}dydx=PoD_t^y \qquad (1)$$

where $p(x,y)$ is the *posterior* multivariate distribution that represents the unknown to be solved. PoD_t^x and PoD_t^y are the empirically estimated probabilities of distress (PoDs) of each of the banks in the system, and $\chi_{\left[x_d^x,\infty\right)}$, $\chi_{\left[x_d^y,\infty\right)}$ are indicating functions defined with the distress thresholds x_d^x, x_d^y, estimated for each bank in the portfolio. In order to ensure that the solution for $p(x,y)$ represents a valid density, the conditions that $p(x,y)\geq 0$ and the probability additivity constraint $\int\int p(x,y)dxdy=1$, also need to be satisfied. Once the set of constraints is defined, the CIMDO-density is recovered by minimizing the functional:

$$L\left[p,q\right]=\int\int p(x,y)\ln p(x,y)dxdy-\int\int p(x,y)\ln q(x,y)\,dxdy+ \qquad (2)$$

$$\lambda_1\left[\int\int p(x,y)\,\chi_{[x_d^x,\infty)}dxdy-PoD_t^x\right]+\lambda_2\left[\int\int p(x,y)\,\chi_{[x_d^y,\infty)}dydx-PoD_t^y\right]+\mu\left[\int\int p(x,y)\,dxdy-1\right]$$

[25] These stylized facts apply equally to bank and nonbank financial institutions.

where λ_1, λ_2 represent the Lagrange multipliers of the consistency constraints and μ represents the Lagrange multiplier of the probability additivity constraint. By using the calculus of variations, the optimization procedure can be performed. Hence, the optimal solution is represented by a *posterior* multivariate density that takes the form

$$p(x,y) = q(x,y)exp\left\{-\left[1+\mu+(\lambda_1 x_{(x_d^x,\infty)}+(\lambda_2 x_{(x_d^y,\infty)})\right]\right\} \tag{3}$$

From the functional defined in equation (2), it is clear that the CIMDO recovers the distribution that minimizes the probabilistic divergence; i.e., "entropy distance," from the prior distribution and that is consistent with the information embedded in the moment-consistency constraints. Thus, out of all the distributions satisfying the moment-consistency constraints, the proposed procedure provides a rationale by which we select the posterior that is closest to the prior (Kullback, 1959), thereby, solving the under-identified problem that was faced when trying to determine the unknown multivariate distribution from the partial information provided by the PoDs. Intuitively, although a prior distribution is based on economic intuition and chosen in consistency with the SA, it is usually inconsistent with empirical observations. Thus, using the cross-entropy solution, one solves this inconsistency, reconciling in the best possible way the distribution that is closest to the prior but consistent with empirical observations.

Quantification of Losses of Financial Institutions

Once the FSMD is estimated using the CIMDO approach, a Monte-Carlo simulation is performed to generate $\boldsymbol{X}$ random numbers. For every simulation i two cases can initially be considered:

a. If $X_i \leq K_i$ then the FI i has defaulted and $\mathcal{X}_{\left(-\infty, X_d^i\right]} = 1$.

b. If $X_i > K_i$ then the FI i has survived and $\mathcal{X}_{\left(-\infty, X_d^i\right]} = 0$.

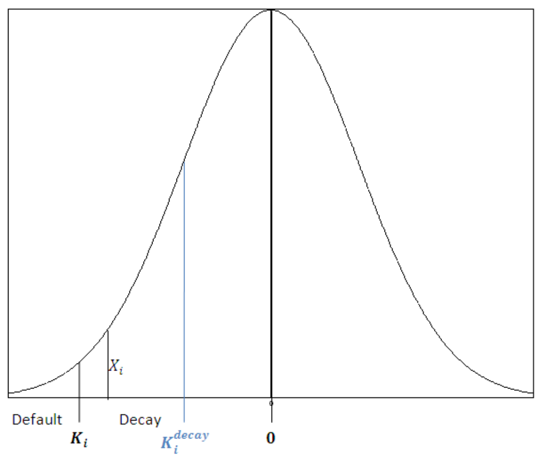
Nevertheless, in addition to the binary case (default or not default) described above, a financial institution can also experience losses if its risk quality gets deteriorated with respect to its current state.

Therefore, from simulated log asset returns, it is possible to characterize implied deteriorations in the risk quality of FIs asset values. In order to capture this effect, we map losses to the returns if they fall into a decay zone (lower risk quality zone). Hence, if a return falls in the decay zone, then a loss will be assigned to this return, which is proportional to the severity of the return. If we define the decay threshold for a given FI as K_i^{decay} then we will now define the random variable Y_i as follows:

$$Y_i = \begin{cases} 0 \; if \; X_i > K_i^{decay} \\ \dfrac{\phi_i\left(K_i^{decay}\right) - \phi(X_i)}{\phi_i\left(K_i^{decay}\right) - \phi(K_i)} \; if \; K_i < X_i < K_i^{decay} \\ 1 \; if \; X_i < K_i \end{cases}$$

where ϕ_i is the cumulative distribution function of the returns of FI B_i. (Figure 6).

Loss Thresholds



Lastly, for each of the ***X*** simulations, computation of losses of the portfolio of FIs is done by adding up the losses implied by each FI. Note that losses incurred by each FI are estimated by multiplying their "exposure at default" (EAD) by their "loss given default" (LGD). Once quantification of losses for individual loans are defined, portfolio losses are estimated, as the sum of the individual losses in a portfolio. Portfolio losses are then estimated for each of the *m* simulations. Then a histogram is made with the *m* simulated portfolio losses. This histogram characterizes the portfolio loss distribution (PLD).

Then, for each simulated X_i, representing the returns of a given FI i, losses are defined as:

$$LGD_i \cdot EAD_i \cdot Y_i \quad ,$$

Where LGD_i is the loss given default, and EAD_i represents the exposure of the system to a given FI. Therefore, EAD_i is quantified by the total assets of each FI at a given time *t*.

Once the quantification of losses for individual FIs are estimated for each of the *m* simulations, a histogram is made with the *m* simulated losses. This histogram characterizes the individual institutions' loss distribution (IPLD), from which the quantification of extreme losses for each individual institution can be done. This is achieved by estimating the Value at Risk (VaR) of the ILPD (at a given confidence level).

Appendix III. Quantification of the Marginal Contribution to Systemic Risk

The MCSR requires the estimation of losses at the systemic level and the estimation of the Shapley value from these losses.

Simulation of Systematic Losses

Once the losses for each individual FI are estimated as described in Appendix II, these losses are aggregated to generate the FI portfolio's loss distribution, which characterizes the financial system's extreme (unexpected) losses. These losses represent the extreme losses that the system can have at a given confidence level, which are characterized by a Value at Risk or an Expected Shortfall amount.

Quantification of the Shapley Value

From the distribution of systemic losses it is possible to estimate the level of systemic risk by the use of the Value at Risk (VaR) or Expected Shortfall (ES). From these, it is possible to estimate the Shapley Value of a financial institution, a metric that measures the importance of a financial institution in the financial system; i.e.,; it MCSR, taking into account the FIs interconnectedness with the system and its relative size.

Value at Risk

The α-VaR of a loss distribution is given by the smallest number ξ such that the probability that the loss L exceeds ξ is not larger than$(1-\alpha)$. Mathematically:

$$\alpha - VaR(L) = inf\{\xi \in L\colon \mathbb{P}(L > \xi) \leq 1-\alpha\}.$$

Expected Shortfall

The α-ES of a loss distribution is the expected value of the α-tail distribution. We can compute it using the next proposition:
Proposition: Suppose that the probability measure $\mathbb{P}$ is concentrated in a finite number of points y_k in Y. For each $x \in X$ the loss distribution L is a staircase function with jumps in the points $z_1 < z_2 < \cdots < z_N$ and with p_k the probability ok z_k. Let k_α the unique index such that:

$$\sum_{k=1}^{k_\alpha} p_k \geq \alpha > \sum_{k=1}^{k_\alpha - 1} p_k.$$

The α-ES of the loss distribution is given by:

$$\alpha - \mathrm{ES}(x) = \frac{1}{1-\alpha}\left[\left(\sum_{k=1}^{k_\alpha} p_k - \alpha\right) z_{k_\alpha} + \sum_{k=k_\alpha+1}^{N} p_k z_k\right].$$

Shapley Value

The Shapley value was originally developed in the context of cooperative game theory. Given a total payoff which is the generated by the collective effort of all the players, the Shapley value decomposes it with the purpose of dividing it to each player according to their corresponding contribution.

Suppose that we have a measure of systemic risk (VaR or Expected Shortfall) applicable to any sub-group of a financial system S. When we want to create a model of macro prudential supervision one naturally wonders about the contribution of each institution to the level of systemic risk of the whole financial system; that is to say on the systemic importance of each institution. In this case, the value to divide is the Value at Risk (VaR) or the Expected Shortfall for a given confidence level.

With the Shapley value method we could measure the systemic importance of an institution in a financial system. Supposing that the financial system consists of N institutions, the Shapley value method divides the systemic risk of the whole financial system in N parts corresponding to each institution according to their contribution.

Letting $\boldsymbol{ShB_j}$ denote the systemic importance of the institution B_j we will proceed to give an intuitive interpretation of the concept of the Shapley value.

Suppose that the N institutions are ordered randomly in a line and consider the subgroup S_j that consists of all the institutions up to and including B_j. We define the contribution of the institution B_j as the level of systemic risk of the subgroup S_j minus the level of systemic risk of the subgroup$(S_j - \{B_j\})$. With the definition described above the systemic importance of the financial institution B_j is then the average contribution over all the possible $N!$ orderings of the N financial institutions.

We will now proceed to formalize the intuition presented above.

Consider the following measurable space $(A, \mathcal{A}, \mathbb{P})$ where:
A is the set of all permutations of the N financial institutions.
$\mathcal{A}$ is the sigma-algebra generated by A.
$\mathbb{P}$ is the uniform measure over A.
V is our measure of systemic risk which is a function that goes from $\mathcal{A}$ to the real numbers.
Define the following random variable $\mathrm{X}_j\colon \mathcal{A} \to \mathbb{R}$ as:

$$\mathrm{X}_j(\mathrm{a}) = \mathrm{V}(\mathrm{S}_j) - \mathrm{V}(\mathrm{S}_j - \{B_j\}).$$

Where a is an element of A (therefore a is a permutation) and S_j is as defined above.

We will define the systemic importance of the financial institution $B_j$as:
$\boldsymbol{ShB_j} = \mathbb{E}_{\mathbb{P}}[\mathrm{X}_j]$.

It is important to note that the method distributes all the systemic in the financial system. This is expressed by:

$$\sum_{j=1}^{N} \boldsymbol{ShB_j} = V(S)$$

The Shapley value method divides the systemic risk of the whole financial system in N parts corresponding to each institution. The share allocated to each institution is based on their contribution to the level of systemic risk of the financial system. This distribution also captures the systemic importance of each institution of the financial system.

Next, we provide an example: Let us suppose the financial system consists of three banks: $S = \{B_1, B_2, B_3\}$ with the following characteristic function V:

Sub-Group	**V**
Ø	0
B_1	1
B_2	3
B_3	5
B_1B_2	3.5
B_1B_3	5.5
B_2B_3	7
$B_1B_2B_3$	8.5

Now, in order to clarify the concept let's just calculate the Shapley value for the institution B_1. First, we need to obtain the value of X_1 for all permutations$(3! \ = \ 6)$:

Permutation	**Sub-Group (including B_1)**	$\boldsymbol{X_1}$
$B_1B_2B_3$	B_1	$V(B_1) - V(\emptyset) = 1$
$B_1B_3B_2$	B_1	$V(B_1) - V(\emptyset) = 1$
$B_2B_1B_3$	B_2B_1	$V(B_2, B_1) - V(B_2) = 3.5 - 3 = 0.5$
$B_3B_1B_2$	B_3B_1	$V(B_3, B_1) - V(B_3) = 5.5 - 5 = 0.5$
$B_3B_2B_1$	$B_3B_2B_1$	$V(B_3, B_2, B_1) - V(B_3, B_2) = 8.5 - 7 = 1.5$
$B_2B_3B_1$	$B_2B_3B_1$	$V(B_2, B_3, B_1) - V(B_2, B_3) = 8.5 - 7 = 1.5$
		$\boldsymbol{ShB_1} = \mathbb{E}_{\mathbb{P}}[\mathrm{X}_1] = 1$

Note that the Shapley value for the institution B_1 is just the arithmetic mean (because $\mathbb{P}$ is the uniform measure) of the values of X_1 over all permutations of the financial system $S = \{B_1, B_2, B_3\}$.

Another way to express the Shapley value for this example is:

$$\boldsymbol{ShB_1} = \frac{1}{6}\{2[V(B_2, B_1) - V(B_2)] + [V(B_2, B_1) - V(B_2)] + [V(B_3, B_1) - V(B_3)] + 2[V(B_3, B_2, B_1) - V(B_3, B_2)]\}.$$

In general, for a system of N institutions, the expression for the Shapley value of any institution j is given by:

$$\boldsymbol{ShB_j} = \frac{1}{N!} \sum_{\substack{m=1 \\ |S_j|=m}}^{N} (m-1)!\,(N-m)!\left[V(S_j) - V\left(S_j - \{B_j\}\right)\right].$$

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