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Stress Testing Credit Risk: The Great Depression Scenario

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Abstract

By using Moody's historical corporate default histories we explore the implications of scenarios based on the Great Depression for banks' economic capital and for existing and proposed regulatory capital requirements. By assuming different degrees of portfolio illiquidity, we then investigate the relationship between liquidity and credit risk and employ our findings to estimate the Incremental Risk Charge (IRC), the new credit risk capital add-on introduced by the Basel Committee for the trading book. Finally, we compare our IRC estimates with stressed market risk measures derived from a sample of corporate bond indices encompassing the recent financial crisis. This allows us to determine the extent to which trading book capital would change in stress conditions under newly proposed rules. We find that, typically, banking book regulation leads to minimum capital levels that would enable banks to withstand Great Depression-like events, except when their portfolios have long average maturity. We also show that although the IRC in the trading book may be considerable, the capital needed to absorb market risk related losses in stressed scenarios can be more than twenty times larger.

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JEL Classification: G11, G21, G22, G28, G32.

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1. Introduction

The 2007-2009 financial crisis highlighted how market events can be both extreme and difficult to predict. The inability of risk measurement models to forecast such events is often ascribed to their short term focus. Popular conditional volatility models, adopted in commercial risk management software, tend to give more weight to recent observations under the assumption that the recent past is more informative in predicting the future.[2] Although this may be true under normal market conditions, it may not apply in periods of market turmoil. As a result, regulators have recently re-emphasized the need to couple standard risk measurement tools with stress tests designed to capture severe but plausible events (Basel Committee on Banking Supervision (BCBS) 2009a,b,c,d,e,f, Committee of European Banking Supervisors (CEBS) 2009, and Financial Services Authority (FSA) 2009).

Hypothetical stress tests can be designed to simulate rare events but, typically, under assumptions about the distribution of future outcomes and/or the factors influencing such outcomes. In addition, it is often questionable to what extent extreme hypothetical scenarios may reflect realistic occurrences. An alternative to hypothetical stress testing are historically based stress scenarios that aim to reproduce specific past crisis events. Among the main advantages of historical scenarios are the fact that they are plausible, if only because they have occurred before and, in comparison to risk management models, are far less sensitive to model risk. Their main limitation is that often the history of relevant events and/or factors is relatively short. Short histories are sometimes the result of a modeller's choice in order to avoid structural breaks that are produced by changing regulatory, legal and business environment and by financial innovation (Alexander and Sheedy, 2008). Haldane (2009) however, convincingly argues that the "realism" or "plausibility" of a crisis, and by extension of a stress test, crucially depend on a long observation period. Indeed the sheer abnormality of the 2007-2009 crisis when analysed within the context of short term pre-crisis indicators, becomes far more plausible when put into a longer historical context.

[2] See, for example, JPMorgan/Reuters (1996).

In this study, we estimate credit losses for individual corporate exposures with given rating and maturity and for representative bank portfolios. The losses are derived through historical stress tests that take into account a period of almost 90 years. For the purpose, we use Moody's corporate bond and loan default data which, to our knowledge, is the longest historical record of such kind and includes the most severe credit event in recent history, the Great Depression. Such a scenario, which would probably have been considered irrelevant before the default of Lehman Brothers in 2008, has became more relevant since. As noted by Eichengreen and O'Rourke (2009), while the crisis was unfolding it bore remarkable similarities with the events in the 1930s. In addition, IMF's predictions (see Figure 1) show that the level of commercial loan charge offs in the United States in 2010 is not expected to be far from that experienced in the early 1930s. Furthermore, anecdotal evidence suggests that the Great Depression as a central stress scenario may be gaining popularity in the industry[3].

The Basel Committee has recently issued a consultative document (BCBS 2009f) that highlights principles for sound stress testing in the attempt to address the shortcomings of pre-crisis stress testing practices. Among the chief weaknesses identified by the Committee are, (1) low severity and short lived scenarios compared with the magnitude and time persistence of the crisis, (2) the correlation across and within asset classes was underestimated, (3) system-wide interactions (i.e. systemic risk) and feedback effects were largely ignored. Considering the Great Depression scenario allows us to address these concerns: (i) The Depression was both sever and long lasting, and (ii) by deriving credit losses on the basis of historical default rates, correlation and feed-back effects are automatically taken into account.

Carey (2002) derives, with a re-sampling method, the default loss distribution of a "numeraire" portfolio, specified by the Basel Committee, under several stress scenarios, including the Great Depression. He then obtains the minimum levels of capital that banks

[3] For instance, on October 21st 2008, Mark Tucker, chief executive of Prudential, a global insurance company, in an interview with the Financial Times stated that the Great Depression is one of the stress scenarios Prudential consider in order to test the resilience of their capital position.

should hold to survive a Great Depression scenario at various confidence levels. With a simpler framework and a focus on the worst case scenario we extend Carey's work in several ways: (1) we generalize Carey's default-mode approach by including in our analysis migration risk, which is consistent with current and proposed Basel II regulation; (2) we derive counter-cyclical capital buffers based on the Great Depression scenario and illustrate their behaviour over the 1920-2008 sample period; (3) we explore the interaction between liquidity and credit risk in the trading book; and (4) we compare our stress test estimates of credit risk capital with current and proposed bank capital requirements for both the banking book and the trading book.[4]

Historical stress scenarios have recently been proposed to quantify the capital buffers that would help banks to withstand a severe financial crisis (FSA 2009 and CEBS 2009). In a recession, banks are subject to two sources of strain on their capital reserves (1) accumulating losses (2) increasing minimum capital requirements. The latter results from the "procyclical" nature of risk sensitive regulatory capital. Their combined effect may lead to a capital shortage. As a consequence, banks may be forced to cut down on lending, thus causing or exacerbating a credit crunch.[5] In this study we abstract away from the procyclicality of capital requirements, which has been extensively investigated in previous research,[6] and focus on the cyclical behaviour of bank capital due to accumulating losses. Specifically, we look at the capital buffer that a bank should hold to be able to weather the losses that would result in a Great Depression like scenario. To be counter-cyclical, the buffer can be defined as the difference between the historical worst case credit loss and the current loss. This way, buffers expand in a boom when banks can

[4] "A trading book consists of positions in financial instruments and commodities held either with trading intent or in order to hedge other elements of the trading book … Positions held with trading intent are those held intentionally for short-term resale and/or with the intent of benefiting from actual or expected short-term price movements or to lock in arbitrage profits, and may include for example proprietary positions, positions arising from client servicing (e.g. matched principal broking) and market making." (Basel 2006, para. 685 and 687 p. 158). The banking book includes all other assets, mainly unsecuritized loans, but also long term investments in tradable instruments.

[5] "The concern that write-downs would gradually deplete capital buffers has materialised leaving a number of institutions with a need for external capital injections. The recessionary phase increases the likelihood that capital requirements shoot up as a consequence of borrowers' downgrades, possibly leading to a credit crunch." CEBS (2009).

[6] See Ervin and Wilde (2001), Kashyap and Stein (2004), Purhonen (2002), Rösch (2002), and Cosandey and Wolf (2002), Estrella (2004), Catarineu-Rabell et al. (2005), Peura and Jokivuolle (2004) and Gordy and Howells (2006) among others.

more easily and cheaply set aside capital reserves, and contract in a trough, to allow for losses to be absorbed. Counter-cyclical capital buffers based on historical worst case scenarios are also investigated in CEBS (2009). However in their analysis, CEBS (2009) employ a shorter sample period which does not include the Great Depression scenario.

There is a growing literature on stress testing as applied to credit risk. This has been partly motivated by (1) the increased emphasis on stress testing in the new Basel Accord, (2) the renewed effort in this area by central banks and regulators following the introduction of the IMF and World Bank's Financial Sector Assessment Programs in 1999 and (3) increasing academic interest as a result of the 2007-2009 crisis. Bangia et al (2002) Pesaran, Schuermann, Treutler and Weiner (2006), Jokivuolle, Virolainen, Vahamaa (2008) and Huang, Zhou and Zhu (2009) among others, as well as central banks and national regulators[7] have proposed models that seek to explain credit risk indicators using macro-economic variables. Credit stress scenarios are then introduced through shocks to these variables. However, the complexity of the interactions and feedback effects among the real economy and the financial sector may easily lead to substantial model risk which is difficult to quantify ex-ante (Alfaro and Drehmann 2009). By employing historically observed credit risk indicators, such as default rates and migration rates, we do not specify their formal relationship with macro-variables. Instead, we exploit the implicit relationship embedded in the historical data. Estimates of credit losses in stress conditions are then derived directly by identifying crisis scenarios, such as the Great Depression.

We find that current banking book capital requirements may be sufficient to protect banks against Great Depression-like scenarios, except for long maturity portfolios. However, although Great Depression-like losses would not exhaust regulatory capital, they would dent it considerably across all maturities and credit ratings. This implies that the buffers needed to preserve the required minimum levels of capital would be substantial. We also show that the new incremental (credit) risk charge (IRC) for the trading book may require an increase of current trading book regulatory capital by up to 82%. But, when taking into

[7] See Foglia (2008) for a comprehensive survey of the macro credit risk models adopted by several national authorities.

account the level of market risk in the recent crisis, which we estimate for selected portfolios of corporate bonds, trading book capital may need to rise more than five times from the current level to provide banks with adequate protection. This is because, during a crisis, market risk losses far outweigh the incremental credit risk losses captured by the IRC. Indeed, we find that depending on the average rating and maturity of the portfolio the former type of losses can be 2.5 to 22 times larger than the latter. Finally, we observe that the impact of liquidity risk on credit losses in the trading book crucially depends on the rating philosophy adopted by the bank (i.e. point-in-time versus through-the-cycle).

The paper is organised as follows. In Section 2 we (a) introduce the model we employ to estimate credit losses under historical stress scenarios; (b) present a formal comparison between our model's banking book capital estimates and the internal rating based approach in Basel 2; and (c) describe our method to estimate the IRC under proposed new rules for the trading book. In Section 3 we present the data used for our analysis. Results are discussed in Section 4. Section 5 concludes the paper.

2. The model

Regulatory capital under the internal rating based (IRB) approach in Basel II is defined as the "unexpected" credit loss. This is the difference between the expected credit loss conditional on a stress scenario (i.e. a downturn) and the unconditional expected loss. The latter is typically estimated as the average loss over at least a full business cycle. Similarly, we use our model to derive expected credit losses under stress - specifically we look at worst case losses - and average expected losses. Let i denote worst case (W) or average (A), V_i the price of the exposure under scenario i, and G the price of a risk free asset with the same cash flows as V_i. Then, the expected default loss for a corporate exposure held until maturity can be defined as the expected fall in the exposure's value due to default risk. The fall is measured as the relative distance between V_i and G,

$$L_i = \frac{G - V_i}{G} = 1 - \frac{V_i}{G} \qquad \text{for } i = W, A \tag{1}$$

For simplicity, we shall assume that our exposures have the cash flow structure of plain vanilla corporate bonds. Elton et al (2001) compute the price $V_{i,t,g}$ of a corporate bond with coupon C, *n* years to maturity and credit rating *g*, with the following iterative equation,

$$V_{i,t,g} = \frac{a_i P_{i,t+1,g} + \left(C + V_{i,t+1,g}\right)\left(1 - P_{i,t+1,g}\right)}{1 + f_{t,1}} \quad \text{for } t = 0,\ldots,n-1 \tag{2}$$

where a_i is the recovery rate under scenario i, $P_{i,t,g}$ is the probability of default in period *t* conditional on no bankruptcy in an earlier period, $f_{t,1}$ is the one-year zero-coupon risk free forward rate at time *t*, and $V_{n,n}$ is the par value of the exposure which is set to 1. The numerator of (2) is simply the expected value of the bond at time $t+1$. This is given by the value of the bond in the non-default state $\left(C + V_{i,t+1,g}\right)$ multiplied by the survival probability $\left(1 - P_{i,t+1,g}\right)$ plus the value of the bond in the default state, which equals its recovery value $a_i V_{n,n} = a_i$, multiplied by the default probability $P_{i,t+1,g}$. The equation is solved backward from $t = n-1$ to $t = 0$ to arrive at today's price $V_{i,0,g}$.

The default probabilities employed in (2) are not risk neutral but "physical" unlike in conventional risk neutral pricing. Elton et al (2001) use the risk neutral valuation framework with physical default probabilities in order to isolate the expected default loss component from bond spreads. This way, all other spread components, namely, tax premium, market risk premium and liquidity premium[8] are filtered out. Similarly, with (2) we seek to estimate the value of a corporate bond for a risk neutral investor when only default risk is priced. By doing so, the losses we derive with (1) will measure default risk alone. We employ this approach with average and worst case physical default probabilities, $P_{A,t,g}$ and $P_{W,t,g}$, in order to determine the expected default loss under

[8] For an extension of the analysis of Elton et al (2001) to capture the liquidity premium of credit spreads see, for example, Perraudin and Taylor (2003).

average as well as worst case default scenarios. The consistency of this method with the IRB approach in Basel II is shown in Section 2.1.

To implement pricing equation (2) we need to derive the conditional default probabilities $P_{i,t,g}$.[9] These can be computed from cumulative default probabilities $CP_{i,t,g}$. $P_{i,t,g}$ is then the ratio of the unconditional probability of default in period *t*, given by $CP_{i,t,g} - CP_{i,t-1,g}$, and the probability of no default in an earlier period, which is $1 - CP_{i,t-1,g}$,[10]

$$P_{i,t,g} = \frac{CP_{i,t,g} - CP_{i,t-1,g}}{1 - CP_{i,t-1,g}} \qquad \text{for } t \geq 2 \tag{3}$$

Note that for *t* equal 1, $P_{i,1,g} = CP_{i,1,g}$. The next step would be the estimation of the cumulative default probabilities. These in turn are influenced by migration risk. Migration risk can be accounted for through the use of rating transition matrices. Specifically, $CP_{i,t,g}$ can be obtained from the default column of a transition matrix $M_{0,t}$ that includes migration and default probabilities that cover a period of t years from time 0. Under the heterogeneous Markov chain assumption, $M_{0,t}$ can be built from one-year transition matrices estimated over the period of interest,

$$M_{0,t} = \prod_{\tau=0}^{t-1} M_{\tau,1} \tag{4}$$

In this we depart from Elton et al (2001) in that they obtain cumulative default rates with the homogeneous Markov chain assumption, which implies that $M_{\tau,1}$ in (4) does not

[9] Note that the subscripts "*i*" and "*t*" of the probability $P_{i,t,g}$ are two time indicators and hence the probability can be conditional or unconditional with respect to both. The subscript "*i*" relates to time over the sample period, while *t* relates to time over the life of the exposure when the cash flows occur. So, for example, $P_{A,t,g}$ is a probability that is conditional on time t in the life of the exposure and unconditional (i.e. average) with respect to the sample period.

[10] For more details on this see Hull (2006), p. 482.

change over time. While this may be appropriate when computing long term average cumulative default rates as done by Elton et al (2001), it would not be desirable when deriving cumulative default rates in a stress scenario. This is because stress scenarios are characterised by substantial volatility in annual default rates which can only be adequately captured by making $M_{\tau,1}$ time varying. The assumption of time heterogeneity is employed, for example, in CreditPortfolioView, a credit risk model proposed by McKinsey consulting.[11] Bluhm and Overbeck (2007) show how heterogeneous Markov chains can be successfully used to fit the term structure of default rates.

In order to implement historical stress tests going back to the Great Depression we would need to derive the worst case loss L_W and the average loss L_A as defined in (1). To do so, we require estimates of one-year transition matrices $M_{\tau,1}$ each year over the whole sample period. Moody's provide an *average* one-year transition matrix between 1920 and 2008 (reproduced in Panel A of Table 1 from Moody's Investors Service, 2009). However, *annual* one-year transition matrices from 1920 are not publicly available. On the other hand, annual default probabilities are. So, a simple way to derive historical one-year transition matrices would be to replace the default probabilities in the 1920-2008 average matrix with those observed each year in the sample period. Of course, upon changing default probabilities in the average matrix, one should also adjust the non-default probabilities in order to maintain the matrix's internal consistency. Then, the generic *t*-year transition matrix can be defined as follows,

$$M_{0,t} = \prod_{\tau=0}^{t-1} \left[M_{ND,\tau,1} \vdots M_{D,\tau,1} \right] \tag{5}$$

where, $M_{D,\tau,1}$ is the default vector which includes the default probabilities (for all ratings) observed in year τ. $M_{ND,\tau,1}$ is the 1920-2008 average transition matrix with the exclusion of the default vector (i.e. the last column), and with probabilities in the main diagonal (i.e. the probabilities that indicate the likelihood of retaining the initial rating)

[11] See Crouhy et al 2000, equation 40.

adjusted so that the sum of each row of the modified transition matrix $\left[M_{ND,\tau,1} \vdots M_{D,\tau,1}\right]$ is 1.[12]

It may be argued that using the 1920-2008 average one-year transition matrix for the non-default transition probabilities (i.e. for the block matrix $M_{ND,\tau,1}$) may lead to underestimation of the expected default loss in a downturn scenario because downgrade probabilities may be higher in stress periods than during average periods. We address this point by testing the sensitivity of our results when instead of using the average 1920-2008 matrix, we derive $M_{ND,\tau,1}$ with transition matrices estimated in recession periods.

2.1 Comparison with the IRB in Basel II

The model presented in the previous Section allows us to obtain the worst case loss L_W and the average default loss L_A of an individual exposure with a given rating, recovery rate and maturity. A measure of economic capital would then be the difference $L_W - L_A$. Under the IRB of Basel II, the minimum credit risk capital requirement is determined in a similar fashion. Specifically, the IRB capital requirement $K_{z,g}$ for a wholesale corporate exposure z with rating g will be,

$$K_{z,g} = CF \cdot MA_{z,g} \cdot \left[\left(1 - a_z^{IRB}\right)P_{D,1,g} - \left(1 - a_z^{IRB}\right)P_{A,1,g}\right] \cdot EAD_z \qquad (6)$$

where CF is a calibration factor introduced to “broadly maintain the aggregate

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[12] This way of adjusting $M_{ND,\tau,1}$ is the most conservative approach, that is the one that produces, in most cases, the highest downturn credit losses. The alternative would be to adjust all the non-default probabilities in each row of the matrix proportionally to their value. This, which is a popular procedure to re-scale transition probabilities after the exclusion of withdrawn ratings (see, for example, Bangia et al 2002), would be inappropriate in this context. In a crisis period, the default vector $M_{D,\tau,1}$ would include default rates that are higher than those in the 1920-2008 average transition matrix. Then, adjusting all the transition probabilities to the non-default state would lead to downgrade probabilities that are lower in the crisis scenario than on the average scenario, which is difficult to justify. As a robustness check we have also estimated worst case default losses with the latter method and the difference in our results is, however, negligible.

level of [minimum capital] requirements" to the pre-Basel II level;[13] $MA_{i,g}$ is a "maturity adjustment" employed to rescale the capital charge to make it an increasing function of the exposure's duration;[14] $P_{D,1,g}$, the probability of default under a stress scenario (termed "downturn PD"), is computed as a function of the average default probability $P_{A,1,g}$ with a pre-specified formula (see Vasicek 2002 and Gordy 2003); EAD_z is the exposure at default for asset z; and a_z^{IRB} is the recovery rate. For more details about (6) see, for example, Resti and Sironi (2007). Then, for a one-year exposure and an EAD_z normalised to 1, the corresponding measure for the difference $L_W - L_A$ in our model is given in the IRB through the difference of the terms inside the square brackets in (6), i.e. $\left(1-a_z^{IRB}\right)P_{D,1,g}$, which represents the expected loss in a downturn, and $\left(1-a_z^{IRB}\right)P_{A,1,g}$, the average expected loss.

It is easy to show that, for a 1-year exposure, the economic capital resulting from the model illustrated in the previous Section and the IRB capital are consistent with one another. To see this, we need to "harmonise" the assumptions in the model and the IRB approach, which differ in several respects: (1) The model produces worst case and average default losses by taking into account the term structure of interest rates, while interest rates are not explicitly considered in the IRB formula; (2) Unlike in our model, the recovery rate in the IRB formula is the same for the stress and average scenarios; (3) The recovery rate in the IRB is expressed as a percentage of the EAD, which may include both principal and interest. This differs from the definition of recovery used in the bond market and adopted in our model whereby the recovery rate is a percentage of the par value. To show the consistency of our model with the IRB let us then (i) assume zero interest rates and (ii) a constant recovery rate in our model, i.e. $a_W = a_A = a$, (iii) express the IRB recovery in terms of our model's recovery, that is $a_z^{IRB} = a/(1+C)$, and (iv) ignore the calibration factor *CF.* As a result, economic capital based on our worst

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[13] Basel Committee (2006), page 4, paragraph 14.
[14] In the IRB, the maturity of an asset is expressed as "effective maturity" which is computed with a formula that approximates Macaulay duration (see BCBS 2006, p. 75)

case and average default loss and IRB capital for a one-year exposure become remarkably similar,

$$L_W - L_A = \frac{\left(P_{W,1,g} - P_{A,1,g}\right)\left(1 + C - a\right)}{1 + C} \qquad \text{(model)}$$

$$\frac{K_{z,g}}{EAD_z} = \frac{\left(P_{D,1,g} - P_{A,1,g}\right)\left(1 + C - a\right)}{1 + C} \qquad \text{(IRB)}$$

For maturities longer than one year the model and the IRB depart from one another due to their different approach to accounting for maturity effects. The main advantages of our model over the IRB is that, while it retains a simplicity and ease of implementation comparable to the IRB, it also allows one to explicitly take into account (1) the term structure of default rates, (2) the term structure of interest rates and (3) migration risk.

2.2 Holding period and marking to market

The IRB capital requirement was derived with a value-at-risk model under the assumption of a 1-year holding period. The holding period reflects the length of time the bank is exposed to the risk of default of a specific borrower. However, the IRB capital is also influenced by a maturity adjustment, which causes capital to increase for exposures with a maturity longer than 1 year. This can be interpreted as a mark-to-market adjustment, which is meant to capture the additional capital that would be needed beyond the 1-year horizon to account for rating downgrades (BCBS 2005). In essence, then, the holding period is extended to reflect the maturity of the exposure. The model illustrated in Section 2 is consistent with this mark-to-market approach and produces expected credit losses based on the assumption that exposures are held to maturity.

2.3 Default loss sensitivity to interest rates

The default loss in equation (1) (whether worst case or average) depends on the ratio V_i/G. Both, the price V_i of the corporate exposure and the price G of the riskless asset, depend on interest rates. Since, by construction, both exposures have the same cash flows, the sensitivity of the riskless asset to interest rates, that is, its duration, is necessarily higher than that of the corporate exposure. This is because, all else equal, duration increases when the yield of the exposure falls, and the yield of the riskless asset must be lower than the corporate exposure's yield. It follows that as interest rates increase, the ratio V_i/G also increases because G will fall more than V_i. As a result, the default loss $1-V_i/G$ will fall. When implementing our model we shall take a conservative approach whereby interest rates are set to zero and hence default losses are maximised. We do so because (1) being conservative when estimating losses is inherently consistent with the idea behind stress testing, and (2) we can then resolve in a simple way the arbitrary choice of a given term structure of interest rates.

2.4 Incremental credit risk in the trading book: the IRC

Among the lessons one may draw from the recent crisis is that trading book exposures, which are typically held for the purpose of short term resale, may become illiquid. Banks are then forced to hold on to their trading book securities for longer than expected. The result of extended holding periods is that the risk of losses due to default increases. Thus, credit risk, which plays a minor role in the trading book in normal market conditions, may become an important risk factor in a crisis. As a consequence, the Basel Committee has recently finalised the Incremental Risk Charge (IRC), an additional capital requirement for specific exposures in a bank's trading book.[15] The IRC requires "banks that model specific risk to measure and hold capital against default risk that is *incremental* to any default risk captured in the bank's value-at-risk model."[16] The IRC was also introduced to harmonise the treatment of credit risk in the banking and trading books of the bank[17] and thus minimise opportunities for regulatory capital arbitrage, the

[15] The IRC applies to those exposures that are "subject to a capital charge for specific interest rate risk, with the exception of securitization exposures and n-th-to-default credit derivatives" (BCBS 2009b, par. 718(xcii), p. 20).
[16] See BCBS 2009C, p.1.
[17] To this effect the Basel Committee states that "[t]he bank must demonstrate that the approach used to capture incremental risks [i.e. the IRC] meets a soundness standard comparable to that of the IRB approach for credit risk ..." (BCBS 2009b, par. 718(xciii), p. 20).

practice of allocating assets to one book rather than the other to attract lower capital requirements.

The IRC must reflect both default risk and migration risk. "[N]o specific approach for capturing the [IRC] is prescribed" by the Basel Committee (BCBS 2009b, par. 718(xcii), p. 20) which leaves broad discretion to financial institutions. We employ our stress testing model to produce tentative estimates of this capital charge and compare it with the other components of the market risk capital requirement under the internal model approach: (1) the market value-at-risk and (2) the newly proposed stressed value-at-risk (BCBS 2009b, par. 718(lxxvi), p. 13-15).

2.4.1. The liquidity horizon

The IRC "should be based on the assumption of a constant level of risk under the one-year capital horizon" (BCBS 2009c, p.3). This means that the portfolio should be rebalanced to preserve its credit rating profile and concentration level. The rebalancing period, called liquidity horizon, should not be less than three months and can be exposure specific. The higher the concentration of the portfolio on one exposure the longer should be its liquidity horizon. Therefore, the liquidity horizon can be used to account for both liquidity risk as well as concentration risk.

The model proposed in Section 2 can easily accommodate the introduction of liquidity horizons. To do so, one needs to allow for migration risk (i.e. upgrades and downgrades to non-default states) to take place only within the liquidity horizon. Default risk, on the other hand, will always be estimated over one year (the so called "capital horizon"). We use the following procedure to measure the impact of different liquidity horizons on one-year default rates:

1. Estimate the generator matrix Q from a one-year transition matrix $M_{0,1}$. To do so, we follow the procedure illustrated in Israel, Rosenthal and Wei (2001),

$$Q = \sum_{h=1}^{\infty} \frac{\left(M_{0,1} - I\right)^h}{h} \left(-1\right)^{h+1} \tag{7}$$

where I is an identity matrix. As *h* increases, convergence is achieved quickly, so the derivation of the generator does not normally pose computational problems.

2. From the generator, produce a transition matrix over a desired liquidity horizon, say, three months.[18] Let us denote this matrix as $M_{0,0.25}$. Then,

$$M_{0,0.25} = I + \sum_{h=1}^{\infty} \frac{Q^h 0.25^h}{h!} \tag{8}$$

As *h* increases the above summation converges quickly, which implies that the derivation of $M_{0,0.25}$ is straightforward. The cumulative default probabilities $CP_{i,0.25,g}$ in the default column of the resulting matrix will then incorporate the effect of migration risk over the liquidity horizon.

3. Derive one-year default probabilities $CP^{*}_{i,1,g}$ from the default probabilities obtained in the previous Step under the assumption that the portfolio is rebalanced at the end of each liquidity horizon (i.e. every three months). This can be done by cumulating over one year the default probabilities in Step 2 without allowing for migration risk from one quarter to the next,

$$CP^{*}_{i,1,g} = \sum_{v=0}^{3} \left(1 - CP_{i,0.25,g}\right)^v CP_{i,0.25,g} \tag{9}$$

The above equation states that the cumulative one-year default probability is given by the probability of default in the first three-month period $CP_{i,0.25,g}$ plus the probability of default in each of the other quarters when no default has

[18] See Jarrow, Lando and Turnbull (1997) for details.

occurred in any of the previous quarters, $(1 - CP_{i,0.25,g})^{v}\, CP_{i,0.25,g}$.[19]

4. In the last step, we derive credit losses with equations (1) and (2) and the procedure discussed in Section 2. Now, however, historical one-year default probabilities are rescaled to reflect the three month liquidity horizon assumption. This is done by multiplying the historical default probabilities by the ratio $CP^{*}_{i,1,g} / CP_{i,1,g}$ where the denominator is the one-year cumulative default probability (with a one year liquidity horizon) found in the reference transition matrix $M_{0,1}$ employed in Step 1. This type of rescaling is consistent with the approach suggested by CESB (2009). We shall use two reference transition matrices, a through-the-cycle (TTC) matrix and a point-in-time (PIT) matrix, which are characterised by different levels of migration risk. $CP^{*}_{i,1,g} / CP_{i,1,g}$ ratios for different liquidity horizon and transition matrix assumptions are reported in Table 3.

TTC transition matrices are based on TTC ratings that only migrate when a change in the underlying credit quality of the rated entity is considered to be permanent. An example of TTC matrix is the Moody's average transition matrix in Table 1 Panel A. PIT transition matrices, on the other hand, are based on PIT ratings. PIT ratings are more volatile, i.e. tend to migrate more, because they quickly adjust to reflect current changes in credit quality, whether of permanent or temporary nature.[20] In Table 2 we report a sample PIT transition matrix estimated by KMV with company data from 1990 to 1995.[21] By comparing Table 1 Panel A and Table 2 it is immediately clear that in the PIT matrix, transition probabilities to non-default states are far larger (and the probabilities of no-migration far smaller) than in the TTC matrix.

[19] Equation (9) can be obtained by multiplying four times by itself the three month transition matrix $M_{0,0.25}$ computed in Step 2, after setting its transition probabilities to non-default states to zero and the probabilities in the main diagonal to $(1 - CP_{i,0.25,g})$. $CP^{*}_{i,1,g}$ will then be the cumulative default probability of rating g found in the default column of the resulting matrix.

[20] For a discussion of the properties of PIT and TTC ratings see, for example, Loffler (2004).

[21] See Gupton et al (1997), p. 70.

In Table 3 we quantify the influence of liquidity horizons of 1, 3, 6 and 12 months and different transition matrices on one-year default probabilities. In the Table, the one-year default probabilities typically decline as the liquidity horizon gets shorter due to the declining impact of downgrade risk. This holds true for all investment grade ratings. On the other hand, for the worst rating category (CCC) in which, if default does not occur, credit migration can bring a substantial improvement in credit quality, shorter default horizons will increasingly eliminate this substantial upside and as a result bring steadily rising one-year default rates. Results for intermediate categories are more ambiguous (see Panel B).

Substantial differences in the sensitivity to the liquidity horizon are found for PIT and TTC ratings. A comparison between the two Panels in Table 3 reveals that, for investment grade assets, shorter liquidity horizons bring about a greater reduction in one-year default rates with PIT ratings. This is because a greater proportion of default events are preceded by downgrades when PIT ratings are used as opposed to TTC ratings. Then, through portfolio rebalancing, downgraded assets are replaced with higher quality ones at a faster rate for PIT ratings as the liquidity horizon shortens. On the contrary, for the lowest rating category, decreasing migration risk via portfolio rebalancing reduces the potential for upgrades to a greater extent with PIT ratings than with TTC ratings. This results in PIT ratings exhibiting higher default rates at shorter liquidity horizons. The greatest reduction in one-year default rates are found for AAA assets over a 1 month liquidity horizon, which fall by 69.3% when compared with a 12 month liquidity horizon. The largest increase is by 10.8% for CCC assets over a 1-month liquidity horizon. The larges fall (increase) with TTC ratings is for BBB (CCC) by 17.6% (3.2%) over a 1 month liquidity horizon.[22]

[22] It may be argued that the difference between Panel A and B in Table 2 may be due to the fact that PIT and TTC transition matrices differ both in terms of migration probabilities *as well as* default probabilities. We have therefore re-computed Panel B results (not reported) by replacing the default probabilities of the PIT matrix with those of the TTC matrix. Diagonal elements of the PIT matrix have been adjusted to ensure that the sum of the probabilities in each row of the matrix is equal to 1. The new matrix, which differs from that in Panel A only for higher migration risk, but has identical default risk, produces the same patterns observed when comparing Panel A and B.

3. The data

To estimate stress economic capital for the banking book, we evaluate worst case and average default losses, across ratings and maturities. To derive the losses we employ (1) annual default rates for the universe of bonds and loans rated by Moody's in the period 1920-2008 and (2) transition matrices for average and crisis periods from various sources. Default rates for all broad rating categories are shown in Figure 2. For all, except the lowest two categories, the highest default frequency occurred during the Great Depression period. The default rates of B and CCC assets are highly volatile during the 1970s and 1980s and reach their highest peak in that period. However, the number of B and CCC companies rated by Moody's in the 1970s and 1980s is small, compared to the population of higher ratings. As a result, their impact on the aggregate default rate in that period is small. Indeed, when looking at the time series of the one-year aggregate default rate, reported in Figure 3, the Great Depression appears to be, by far, the most prominent default scenario in recorded history. This is also confirmed when the observation period is extended beyond one year. Table 4 shows 1 to 20 year cumulative default rates obtained from 1 year aggregate default rates. The Great Depression period consistently features as the most severe scenario.

In our calculations we use Moody's 1920-2008 average transition matrix as a benchmark (reported in Panel A of Table 1). To test the robustness of our findings and specifically to account for the difference in transition rates between average and crisis periods, we also use the trough transition matrix in Nickell et al (2000) - based on Moody's data for the period 1970-1997 - which we reproduce in Panel B, and the recession transition matrix in Bangia et al (2002) based on Standard&Poor's 1981-1998 data (Panel C). Interestingly, the default rates in these two downturn matrices are higher than in the 1920-2008 average matrix but only for speculative grade assets. With the exception of AAA, which exhibits zero defaults regardless, all the investment grade ratings in Panel B and the top two in Panel C have a lower default rate than in the average 1920-2008 matrix. This reflects the influence on long term averages of the Great Depression which was characterised by abnormally high default rates especially for companies with a high rating.

To compare the size of new and existing capital requirements in the trading book we estimated the IRC, the pre-crisis VaR and the stressed VaR for twelve bond portfolios with different credit rating and maturity characteristics. The portfolios are represented by bond indices sourced from Datastream and spanning two industry sectors, industrial and financial, two rating groups, AAA-AA and A-BBB, and three maturity bands, 5 to 10 years, 10 to 15 years and 15+ years. The sample consists of daily returns over the period May 2004 – August 2009. The period was chosen to include the recent crisis and to allow for enough observations to determine the pre-crisis VaR. Summary statistics are reported in Table 5. All indices exhibit negative skweness (except for the AAA-AA 10-15 year maturity index) and substantial excess kurtosis. Financial indices are almost invariably more negatively skewed and have always fatter tails than industrial indices.

4. Results

In this Section, we present our measures of economic capital for the banking book based on the Great Depression scenario. We then compare economic capital with Basel II regulatory capital. The analysis related to the banking book is concluded with a description of the behaviour of counter-cyclical capital buffers resulting from our stress tests. We then move to the trading book and show our estimates of the IRC based on the default experience in the Great Depression and a predefined liquidity horizon. Finally, we compare the IRC with new and existing elements of trading book regulatory capital to determine the extent of additional capital that banks will be required to hold under new regulation.

In the banking book analysis, we consider plain vanilla bond exposures. As in Elton et al (2001), the bonds' coupon is determined endogenously for every credit rating in such a way that the price of a 10 year bond with that rating equals the bond's par value.[23] In Table 6 we show the default loss in the worst case and average scenarios over the 1920-

[23] Coupon payments are determined by assuming the Moody's average transition matrix over the period 1920-2008 and a recovery rate of 40%. To make the comparison of results more meaningful, the coupon for each rating is kept constant when different recovery rates and transition matrices are used. As a robustness check we have used alternative coupon assumptions and found only second order effects in our results. Specifically, coupons were also implicitly determined in order to set to par the price of bonds with maturities spanning the whole spectrum considered in this study, i.e. from 1 to 20 years.

2008 period as well as the minimum economic capital that would be needed to absorb unexpected credit losses resulting from the worst case scenario. Results are shown across rating categories, from AAA to single-B, several maturities and for different transition assumptions. The worst case scenario coincides with the Great Depression in all except those rating-maturity combinations in the shaded areas (mostly, speculative grade ratings). The CCC rating was dropped for the rating-based analysis because it exhibits anomalous default rate volatility and abnormally high default rates in the early 1980s, both a likely sign of small sample bias. For instance, on average there were 7.2 issuers rated Caa-C by Moody's between 1970 and 1990, with only 2 issuers between 1974 and 1977 and in 1984. This results in very erratic default rates, even in relatively benign periods. For example, between 1980 to 1986, when aggregate default rates were close to the long term historical average, the 1-year default rates for Caa-C issuers, as reported by Moody's, were 33.3%, 0%, 23.1%, 42.1%, 100%, 0% and 26.7%. We recover the CCC rating for the portfolio-based analysis, illustrated below, to replicate the composition of the bank portfolios in Gordy (2000). However, in order to distortions in our results produced by the unreliable CCC default rates in the early 1980s, we derive worst case and average loss by considering a restricted observation period around the Great Depression only (i.e. from 1920 to 1960).

Average default losses are obtained by assuming a mean recovery rate of 45%, which is consistent with the average recovery for senior unsecured bonds reported by Moody's. Worst case losses, given the highly negative correlation between default rates and recoveries (see Figure 4), are computed by assuming a conservative recovery rate of 21%.[24] For simplicity, we shall report our results by using Standard and Poor's letter ratings (AAA, AA, A, BBB, BB, B and CCC) irrespective of the source of default and transition data employed in our calculations. In Panel A of Table 6, average default losses

[24] In this study, we employ recovery rates for senior unsecured corporate bonds as reported in Moody's Investors Service (2009). For the period 1982-2008 issuer-weighted annual average recoveries range from a minimum value of 21.45% in 2001 to a maximum of 62.75% in 1996. The 1982-2008 average is 45.49%. We have also looked at Moody's recovery data for senior unsecured bank loans. However, the sample is much patchier than the bond one and an annual break-down of historical recoveries is not available (except for 2007 and 2008) so that the worst case recovery could not be computed. But, interestingly, in 2008 the issuer-weighted average recovery for senior unsecured loans is 29.8% **-** not far from the worst case observation for corporate bonds **-** and falls to 22.6%, when value weighted, due to a remarkably low recovery (13.6%) on Lehman Brothers defaulted loans.

are produced with the average transition matrix estimated by Moody's over the 1920-2008 period. Worst case losses are the largest default losses in the sample period derived with the same transition matrix but adjusted as described in the model Section. Several patterns are clearly discernible. As is to be expected, both losses as well as economic capital are increasing as the credit rating deteriorates. Both losses also increase with maturity. However, the relationship between maturity and economic capital is not always monotonic. It turns out that for low credit quality assets, the increasing proportion of average losses relative to worst case losses as maturity goes up may become so substantial that economic capital eventually starts to decline (see single-B category in Panel A). This means that banks may be allowed to hold less capital against highly risky assets as maturity increases but only in exchange for higher loan loss provisions.

In Panel B of Table 6 average losses are obtained with the 1970-1997 average one-year transition matrix estimated by Nickell et al (2000). The average losses are slightly smaller than those in Panel A. On the other hand, worst case losses, generated with the trough transition matrix estimated by the same authors during trough business cycle periods between 1970 and 1997, are very similar to those in Panel A. The difference in economic capital between Panel A and B is also small and does not reveal any specific pattern. In Panel C of Table 6 we compute average and worst case losses with the unconditional and recession transition matrices estimated by Bangia et al (2002). As before, expected losses are generally lower than in Panel A. On the contrary, worst case losses and economic capital in Panel C are generally higher than in Panel A.[25]

To present our default loss findings in a more familiar form we also calculate the implied credit spreads associated with each loss for every maturity/rating combination. The resulting term structures of credit spreads under the average and worst case scenarios are

[25] It should be noted that the one-year matrices used to derive average and worst case losses in the three Panels of Table 6, when adjusted as in (5), differ only in their transition probabilities to the non-default states. One-year default probabilities, on the other hand, are common since those of the original matrices are replaced with actual default rates observed over the 1920-2008 sample period. The implication is that the default losses (and as a result economic capital) for the one-year holding period are identical across the three Panels because they only depend on one-year default probabilities and are not influenced by transition probabilities to non-default states. On the other hand, default losses for longer holding periods, being derived with cumulative default rates which in turn are affected by transition probabilities through equation (5), will normally differ.

reported in Figure 5. The spreads are obtained with the Nelson and Siegel (1987) method extended as in Svensson (1995), which allows us to estimate zero coupon yields and hence zero coupon spreads. The most noticeable feature of the estimated spreads is that those under the worst case scenario are by and large downward sloping with the exception of AAA spreads. The downward pattern is the result of the short duration of crisis periods. As it can be seen in Figure 3 even during the most serious trough in the 1930s, high default rates are not persistent. The peak in 1933 (with a default rate of 8.40%) is followed by a sharp drop in 1934 (3.45%) with default rates reverting back to a level close to the 1920-2008 average (1.08%) in 1936 (1.64%). This argument does not apply to AAA as its one-year default rate is unaffected by crisis periods and has always remained equal to zero since 1920.

We now proceed to compare our economic capital estimates with regulatory capital. We do so by computing the ratios of economic capital to minimum IRB capital requirements[26]. The ratios are reported in Table 7 and can be interpreted in two ways. They may indicate (1) how much extra capital, normally referred to as "capital buffer", a bank should hold to absorb worst case losses without breaching its minimum banking book capital requirements, and (2) to what extent minimum requirements would be able to absorb worst case losses in the absence of additional capital buffers. In order to derive IRB capital,[27] the unconditional default probability $P_{A,1,g}$ is estimated as the long term average annual default rate over the whole sample period.[28] This complies with the Basel Committee's requirement of using long-term default probabilities.[29] It also enables us to

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[26] The Basel Committee introduced two IRB approaches (BCBS 2006), foundation and advanced. Banks that qualify for the advanced version can internally estimate recovery rates, maturity and the exposures at default. In this work, we retain the flexibility of the advanced IRB in order to ensure a more meaningful comparison between regulatory capital and the economic capital obtained from our model.

[27] Unlike for economic capital where recovery rates vary for average loss (45% recovery) and worst case loss (21% recovery), IRB capital, according to the Basel II specification, is based on the same downturn recovery rate in both the average and downturn scenario (see equation 7). So, for the IRB capital we shall use a common 21% recovery.

[28] The sample period employed to estimate long term average default rates depends on the transition matrix used in the calculations. As we use three transition matrices to derive average losses, average default rates refer to three distinct sample periods 1920-2007 (Moody's matrix), 1970-1997 (Nickell et al's) and 1981-1998 (Bagia et al's).

[29] The Basel II rulebook states that "Irrespective of whether a bank is using external, internal, or pooled data sources, or a combination of the three, for its PD estimation, the length of the underlying historical observation period used must be at least five years for at least one source. If the available observation

compare capital buffers with static capital requirements based on a *constant* average default probability, $P_{A,1,g}$. As a consequence, we can abstract away from the pro-cyclical behaviour of the IRB capital which results when $P_{A,1,g}$ is estimated over short observation periods. The main finding in Table 7 is that, in most cases, IRB credit risk capital requirements are sufficiently large as to protect the bank against Depression-like scenarios. However, some long maturity assets may be subject to a level of credit risk that is not fully captured by the IRB thus producing a potential capital shortfall. This is because IRB capital is designed to increase up to a 5 year (effective) maturity and remains constant thereafter, while economic capital, as shown in Table 6, normally keeps increasing. Importantly, the largest shortfalls, in relative terms, are observed for investment grade ratings. In addition, it appears that the capital buffers needed to preserve a bank's required minimum capital would be rather substantial across most maturities and ratings if they were to absorb Depression-like losses.

The three panels in Table 7, obtained as before with alternative transition matrices, show similar patters. The largest instances when economic capital exceeds regulatory capital are found, for long maturities, with Bangia et al's transition matrices. This is to be expected given that those transitions produce the largest economic capital at long maturities (see Table 6). The capital shortfall for single-A assets at one-year maturity in Panel B is not due to an abnormally high economic capital but to an unusually low regulatory capital resulting from the low default rates in Nickell et al's average transition matrix, which are used to compute the IRB in Panel B.

The buffers reported in Table 7 are averages over the sample period in that they are computed as the difference between worst case losses and 1920-2008 *average* default losses. However, when formally introduced, the capital buffers will likely be managed by banks dynamically. The buffers will be decreased to absorb losses when they occur and increased back to their original level in tranquil periods when default probabilities are low. To appreciate the counter-cyclical behaviour of buffers managed in this way we

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period spans a longer period for any source, and this data are relevant and material, *this longer period must be used*. [emphasis added]" (BCBS 2006, paragraph 463).

have re-computed them as the difference between worst case loss and the *current* loss estimated each year in the same period. Results for 5 year maturity bonds across the various ratings are reported in Figure 6.[30] Buffers are plotted against the relevant 5-year cumulative default rates. As one would expect, buffers shrink to zero during the Great Depression and are highly negatively correlated with default rates. For AA and BBB, BB and B ratings the greatest fall, with the exclusion of the Great Depression period, takes place in the early nineties. For AAA and single-A the critical years are 2008 and 2002 respectively. Mean and volatility of the buffers increase as credit quality falls. For the middle category, BBB, the mean buffer is 5.22% of the value of the exposure, its highest value is 6.54% and its volatility over the sample period is 1.48%.

We repeat the ratings-based analysis of credit losses and capital buffers discussed above with the four stylised bank portfolios employed by Gordy (2000). These vary in terms of average credit quality and rating distribution and are denoted by “High”, “Average”, “Low” and “Very Low”. The first three are constructed from the distribution of bank portfolios resulting from internal surveys of large bank organizations compiled by the Federal Reserve Board. The last one is a hypothetical portfolio of a very weak large bank during a recession. The portfolios’ rating distributions are shown at the bottom of Table 8. Such distributions allow us to associate a weight to each rating category which corresponds to the relative dollar investment in that rating within each portfolio. Then, portfolio losses at any given point in time are defined as the weighted average of the losses derived at that time for each rating. From the resulting time series of portfolio losses, the worst case and average losses are obtained as the maximum and mean loss respectively. It should be noted that this procedure allows us to take into account default

[30] To derive time dependent capital buffers in the 1920-2008 period, we have computed ratings-based losses with time varying recovery rates. However, Moody’s provide a time series of senior unsecured recoveries for the period 1982-2008 only. We have populated the time series of recovery rates between 1920 to 1981 by exploiting the high negative correlation of recovery and default rates (see Figure 4). We have done so by computing quantiles, at 5% intervals, of the empirical distribution of aggregated default rates (1920-2008) and the distribution of recovery rates (1982-2008). We have then taken each default rate in the 1920-1982 period, identified the closest quantile of the default rate distribution and populated the time series of recovery rates with the complementary quantile of the recovery rate distribution. For example, if the 1920 default rate is closest to the 25% quantile of the aggregate default rate distribution, we have assumed that the 1920 recovery rate would be the 75% quantile of the empirical distribution of recoveries. The resulting correlation of the generated time series of recoveries in the 1920-1981 period and the observed default rates in the same period is -84% which is similar to the correlation of the two series between 1982 and 2008 (-74%).

correlations across ratings since, at any point in time, the portfolio loss will reflect the ratings' empirically observed default rates which embed their default dependence structure at that time. For simplicity, we assume that the number of exposures in each rating category is sufficiently large as to eliminate idiosyncratic deviations of each rating sub-portfolio from observed historical default rates.

All portfolios include assets in the CCC rating category which, as mentioned earlier, appears not to be sufficiently populated in the Moody's sample in the early 1980s. For this reason, worst case and average losses and stressed economic capital for all the portfolios considered are computed with Moody's default histories in the 1920-1960 time interval. Results in Table 8 indicate that the difference in banking book economic capital between high quality and low quality banks may be substantial especially at low maturities. In panel A, where credit losses are derived with the Moody's 1920-2008 average transition matrix, the capital of the very low quality bank is 3.45 times that of a high quality bank for a portfolio with one-year maturity. When we look at 20 year maturity the ratio falls to 1.40. This is because, while the economic capital of the very high quality portfolio steadily increases with maturity, economic capital for portfolios of average or lower credit quality either declines or flattens as maturity increases. This is the result of the increasing importance of the average loss relative to the worst case loss as credit quality deteriorates and maturity increases, which was illustrated before (see discussion of Table 6 results). The pattern is stronger in the portfolio-based analysis than in the ratings-based analysis because portfolios include the CCC category in which the effect of increasing average losses is much more pronounced than in other rating categories. Results in Panel B and C for different transition matrices are consistent with those in Panel A. In Table 9 we report Great Depression-induced capital buffers for the various portfolios as a proportion of IRB capital requirements. We find that the largest buffer, in relative terms, would be needed for the high quality portfolio with longest maturity, in line with our previous observations in the ratings-based analysis.

The last step of our empirical investigation is concerned with the new regulation for the trading book. With our model and Moody's historical default rates, we estimate the proposed incremental credit risk capital requirement in the trading book, the IRC, and compare it with (a) the value-at-risk based trading book capital requirements estimated before the 2007-2009 crisis[31], and (b) with the newly proposed "stressed" value-at-risk which is designed to build into capital requirements a cushion against severe market risk events. The IRC is quantified as the difference between worst case losses from the Great Depression scenario and average losses, as done for the banking book. However, credit losses are now estimated under the assumption of a three month liquidity horizon, by following the procedure illustrated in Section 2.4.1. We estimate pre-crisis VaR and stressed-VaR with the set of bond indices described in Section 3. Results are reported in Table 10. We find that,

1. The IRC capital is significant when compared to the current trading book capital requirement (which is denoted as "old capital" in the Table and based on the pre-crisis 10-day 99% VaR plus specific risk[32]). Its size crucially depends on the underlying rating philosophy used to determine credit risk. With through-the-cycle ratings the IRC ranges from a minimum of 22% of old capital for 5-10 year maturity AAA-AA bonds to a maximum of 82% of old capital for 10-15 year A-BBB bonds. The percentages are significantly lower when looking at point-in-time ratings and stand at 14% and 67% respectively. IRC values across the financial and industrial sectors are identical because we do not have a industry breakdown of the Depression scenario. However, differentiating by industry allows us to capture industry effects in the "stressed" value-at-risk which is discussed in the next point.
2. The stressed VaR, which is based on the maximum 10-day 99% VaR[33] over the whole period covered by the bond sample (May 2004 to August 2009), and hence captures the extent of market risk in the recent crisis, is always significantly larger

[31] One of the earliest signs of the crisis was the failure of Bear Sterns to provide financial support to one of their hedge funds on 22nd June 2007. We estimate pre-crisis VaR with data up to 20th June 2007.
[32] The trading book VaR under the internal model approach for the bank's trading book is computed as the higher of the previous day's 99% Value-at-Risk calculated for a 10 day holding period with 1 year worth of data and the 60-day average of the 10-day 99% VaR multiplied by a factor of 3. We assume that the bank has a model to account for specific risk and this equals the capital charge under the standardised approach.
[33] The stressed VaR is the maximum of the time series of daily VaRs obtained *during a specified stressed period*. Each daily VaR is the higher of the previous day's 99% VaR calculated for a 10 day holding period with 1 year worth of data and the 60-day average of the 10-day 99% VaR multiplied by a factor of 3 (see BCBS 2009b, p. 14-15).

than the IRC. For industrial bonds, stressed VaR ranges from a maximum of 11.2 times the level of the IRC (for 5-10 years AAA-AA bonds) and a minimum of 2.8 times (for A-BBB bonds with maturity greater than 15 years). The ratios between the two risk measures are even larger for financial bonds where they stand at 22.3 times and 3.9 times respectively.

3. As a result of the previous two observations, the newly proposed capital requirements for the trading book, denoted as “new capital” in the Table and given by the sum of pre-crisis VaR, stressed VaR, a specific risk charge and the IRC are much bigger than the current capital requirements. The New/Old capital ratios in the Table allows us to illustrate this point and show that new capital ranges, for industrial bonds, from a minimum of 3.61 times current capital (AAA-AA 15+ maturity bonds) – which corresponds to an increase of 261% - to a maximum of 4.32 times (A-BBB 5-10 year maturity bonds) – an increase of 332%. The multiples are bigger for financial bonds and are 4.72 (372%) and 6.53 (553%) respectively. In other words, following the current crisis, even if risk went back to pre-crisis levels, banks may be required to increase their trading book capital by more than 5 times on the basis of the new rules.

The Basel Committee has recently completed a quantitative impact study on the new proposal for computing trading book capital requirements (BCBS 2009e). The findings reported by 43 participating banks across 10 countries show that trading book capital would increase on average by 102.7% due to the IRC (for a 3 month liquidity horizon) and by 110.8% as a result of the new stressed VaR requirement. Standard deviations around the average are substantial (125.1% and 130.8% respectively). Our analysis shows markedly larger capital increases for stressed VaRs.

5. Conclusion

In this paper, we estimate expected credit losses for individual exposures as well as representative bank portfolios under the Great Depression scenario. We then derive the economic capital measures based on this scenario and compare them with existing and proposed capital requirements for banks’ banking book and trading book. We find that, in most cases, current banking book capital requirements would be sufficient to protect a bank against a Depression-like event. Likely exceptions are long maturity portfolios. However, across most maturities and ratings, the capital buffers that would be needed to maintain banks' capital above the regulatory minimum in a Great Depression scenario, are substantial. Robustness checks conducted by employing rating transition matrices estimated from different data sources confirm our findings. When looking at the new regulation in the trading book we find that the requirement for incremental credit risks, the IRC, may be substantial when compared with existing regulatory capital levels. However, stressed VaRs estimated on corporate bond portfolios during the current crisis show that market risk related losses may be far greater and, depending on the characteristics of the portfolio, be more than twenty times as large as the IRC. The higher capital requirements that will result from the introduction of the new rules, while making banks more resilient in a crisis, are also likely to affect banks' asset allocation decisions and specifically, the balance between banking book and trading book investments. The implications of the proposed regulation for the financial system and the real economy have not been addressed in this study and deserve careful investigation.

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Table 1: Average and Downturn Transition Matrices

Panel A: Moody's average transition matrix, 1920-2008

	Aaa	Aa	A	Baa	Ba	B	Caa-C	D
Aaa	91.1	7.8	0.9	0.2	0.0	0.0	0.0	0.0
Aa	1.3	90.6	7.1	0.7	0.2	0.0	0.0	0.1
A	0.1	3.2	90.2	5.6	0.7	0.1	0.0	0.1
Baa	0.0	0.3	5.0	87.9	5.4	0.8	0.2	0.3
Ba	0.0	0.1	0.5	6.6	83.0	7.5	0.7	1.5
B	0.0	0.1	0.2	0.7	6.8	81.6	6.4	4.3
Caa-C	0.0	0.0	0.1	0.1	0.7	6.5	74.4	18.2

Panel B: Nickell et al's trough transition matrix, 1970-1997

	Aaa	Aa	A	Baa	Ba	B	Caa-C	D
Aaa	89.6	10.0	0.4	0.0	0.0	0.0	0.0	0.0
Aa	0.9	88.3	10.7	0.1	0.0	0.0	0.0	0.0
A	0.1	2.7	91.2	5.6	0.4	0.0	0.0	0.0
Baa	0.0	0.3	6.6	86.8	5.6	0.4	0.2	0.1
Ba	0.0	0.1	0.5	5.9	83.1	8.4	0.3	1.7
B	0.0	0.1	0.2	0.8	6.6	79.7	3.2	9.4
Caa-C	0.0	0.0	0.0	0.5	1.0	7.6	67.7	23.3

Panel C: Bangia et al's recession transition matrix, 1981-1998

	AAA	AA	A	BBB	BB	B	CCC	D
AAA	92.2	6.5	1.2	0.0	0.0	0.0	0.0	0.0
AA	0.7	88.3	10.1	0.6	0.3	0.0	0.0	0.0
A	0.1	3.2	86.8	9.3	0.6	0.0	0.0	0.0
BBB	0.1	0.2	4.0	86.3	8.2	0.6	0.1	0.5
BB	0.0	0.2	0.3	4.9	81.7	9.4	1.6	1.9
B	0.0	0.2	0.2	0.4	2.5	81.7	6.7	8.2
CCC	0.0	0.0	0.0	0.0	0.0	3.5	53.8	42.6

Table 2: KMV Point-in-Time Transition Matrix

	AAA	AA	A	BBB	BB	B	CCC	D
AAA	66.3	22.2	7.4	2.5	0.9	0.7	0.1	0.0
AA	21.7	43.0	25.8	6.6	2.0	0.7	0.2	0.0
A	2.8	20.3	44.2	22.9	7.4	2.0	0.3	0.1
BBB	0.3	2.8	22.6	42.5	23.5	7.0	1.0	0.3
BB	0.1	0.2	3.7	22.9	44.4	24.5	3.4	0.7
B	0.0	0.1	0.4	3.5	20.5	53.0	20.6	2.0
CCC	0.0	0.0	0.1	0.3	1.8	17.8	69.9	10.1

Table 3: Default Probabilities and Liquidity Horizons

	Months			
Capital horizon	12	12	12	12
Liquidity horizon	1	3	6	12
	Panel A: Through-the-Cycle transition matrix: Moody's average 1920-2008			
Credit Rating	Default Probabilities			
AAA	0.00	0.00	0.00	0.00
AA	0.07	0.07	0.07	0.07
A	0.07	0.07	0.07	0.08
BBB	0.25	0.26	0.28	0.31
BB	1.37	1.39	1.42	1.48
B	3.86	3.94	4.07	4.29
CCC	18.79	18.68	18.53	18.21
	Ratios relative to 12 month capital horizon and 12 month liquidity horizon, in percent			
AAA	na	na	na	na
AA	96.17	96.80	97.80	100
A	83.15	86.09	90.61	100
BBB	82.43	85.63	90.44	100
BB	92.54	93.86	95.89	100
B	89.96	92.01	94.89	100
CCC	103.21	102.63	101.76	100
	Panel B: Point-in-Time transition matrix: KMV 1990-1995			
	Default Probabilities			
AAA	0.01	0.01	0.01	0.02
AA	0.01	0.02	0.03	0.04
A	0.06	0.07	0.08	0.10
BBB	0.12	0.16	0.20	0.26
BB	0.72	0.70	0.71	0.71
B	0.74	1.04	1.42	2.01
CCC	11.23	10.96	10.60	10.13
	Ratios relative to 12 month capital horizon and 12 month liquidity horizon, in percent			
AAA	30.66	38.92	55.77	100
AA	33.96	47.51	67.00	100
A	63.88	67.25	75.95	100
BBB	47.07	59.94	76.11	100
BB	100.81	98.38	99.75	100
B	36.85	51.83	70.51	100
CCC	110.82	108.23	104.61	100

Table 4. Worst Time Periods based on Cumulative Default Rates

Cumulative default rates have been computed from the 1920-2008 time series of annual default rates across all rating categories reported in Figure 3.

Length in years	Start	End	Cumulative Default Rate, %
1	1933	1933	8.42
2	1932	1933	13.40
3	1931	1933	16.70
4	1932	1935	19.62
5	1931	1935	22.69
6	1931	1936	23.96
7	1931	1937	25.22
8	1931	1938	26.81
9	1931	1939	27.70
10	1931	1940	29.05
11	1931	1941	29.82
12	1930	1941	30.54
13	1929	1941	31.01
14	1929	1942	31.34
15	1927	1941	31.77
16	1925	1940	32.37
17	1924	1940	33.15
18	1924	1941	33.87
19	1923	1941	34.40
20	1922	1941	35.07

Table 5: Bond Index Summary Statistics

Daily percent returns for the period 7/5/2004-21/08/2009.

	Bond Indices					
	AAA-AA			A-BBB		
	5-10y	**10-15y**	**15+y**	**5-10y**	**10-15y**	**15+y**
			Industrials			
Mean	0.03	0.03	0.03	0.02	0.02	0.02
Volatility	0.39	0.49	0.70	0.37	0.43	0.64
Skewness	-0.05	-0.18	-0.04	-0.34	-0.55	-0.19
Excess Kurtosis	4.74	6.24	2.69	5.47	4.92	2.61
Minimum	-2.34	-3.73	-3.39	-2.26	-3.24	-4.13
Maximum	2.82	3.32	3.67	2.65	2.28	2.90
			Financials			
Mean	0.02	0.02	0.02	0.01	0.01	0.01
Volatility	0.50	0.71	0.80	0.54	0.54	0.71
Skewness	-1.94	0.58	-1.02	-2.00	-0.61	-1.42
Excess Kurtosis	40.34	31.44	12.61	29.39	8.72	13.93
Minimum	-6.56	-7.06	-8.31	-6.44	-4.33	-7.94
Maximum	4.49	8.42	3.87	3.94	3.59	3.10

Table 6: Worst Case Default Loss, Average Default Loss and Economic Capital based on Great Depression Scenario

All figures are in percent. 1920-2008 sample of Moody's default rates. Worst case losses in shaded areas are unrelated to the Great Depression.

	AAA	AA	A	BBB	BB	B
	Panel A: Moody's average transition matrix, 1920-2008					
Maturity	Worst Case Loss					
1	0.00	0.69	1.36	1.57	8.81	15.71
2	0.07	0.73	1.77	2.58	12.75	21.79
3	0.14	1.44	2.16	4.05	14.65	27.22
5	0.40	2.10	3.50	6.63	19.08	34.60
10	1.42	3.75	5.85	11.28	23.92	46.00
20	4.20	7.47	11.42	19.63	33.18	55.10
	Average Loss					
1	0.00	0.03	0.05	0.15	0.59	1.92
2	0.00	0.07	0.11	0.34	1.27	3.95
3	0.01	0.11	0.19	0.57	2.04	6.01
5	0.04	0.21	0.38	1.15	3.79	9.95
10	0.19	0.60	1.20	3.18	8.51	17.97
20	0.92	2.04	3.78	7.94	16.14	27.30
	Economic Capital					
1	0.00	0.65	1.31	1.42	8.22	13.79
2	0.07	0.66	1.66	2.24	11.48	17.83
3	0.13	1.33	1.98	3.48	12.60	21.21
5	0.36	1.89	3.12	5.48	15.29	24.65
10	1.23	3.15	4.65	8.11	15.41	28.04
20	3.28	5.42	7.64	11.69	17.03	27.80
	Panel B: Nickell et al's transition matrices, 1970-1997					
	Worst Case Loss					
1	0.00	0.69	1.36	1.57	8.81	15.71
2	0.07	0.75	1.77	2.53	12.79	21.54
3	0.15	1.49	2.16	3.92	14.73	26.01
5	0.43	2.19	3.47	6.41	19.03	32.03
10	1.48	3.71	5.42	10.62	23.22	41.81
20	3.97	6.78	9.93	17.55	31.44	50.46
	Average Loss					
1	0.00	0.03	0.05	0.15	0.59	1.92
2	0.00	0.07	0.11	0.32	1.23	3.74
3	0.01	0.10	0.17	0.53	1.93	5.47
5	0.03	0.19	0.33	1.00	3.43	8.67
10	0.14	0.49	0.95	2.52	7.31	15.08
20	0.63	1.52	2.75	5.95	13.55	22.71
	Economic Capital					
1	0.00	0.65	1.31	1.42	8.22	13.79
2	0.07	0.68	1.66	2.21	11.56	17.80
3	0.14	1.38	1.99	3.39	12.80	20.54
5	0.40	2.00	3.14	5.41	15.60	23.36
10	1.33	3.22	4.47	8.10	15.90	26.73
20	3.34	5.26	7.18	11.60	17.90	27.75

Table 6: Continued

			Panel C: Bangia et al's transition matrices, 1981-1998			
			Worst Case Loss			
1	0.00	0.69	1.36	1.57	8.81	15.71
2	0.06	0.76	1.77	2.74	13.05	21.97
3	0.13	1.49	2.18	4.43	15.44	28.29
5	0.37	2.23	3.53	7.25	20.35	36.98
10	1.36	4.24	6.42	12.95	30.42	51.54
20	4.64	9.80	14.98	25.69	43.13	62.53
			Average Loss			
1	0.00	0.03	0.05	0.15	0.59	1.92
2	0.00	0.07	0.11	0.34	1.30	3.82
3	0.01	0.11	0.18	0.57	2.09	5.67
5	0.03	0.22	0.38	1.13	3.83	9.10
10	0.16	0.59	1.16	3.02	8.20	15.90
20	0.74	1.82	3.50	7.19	14.77	23.83
			Economic Capital			
1	0.00	0.65	1.31	1.42	8.22	13.79
2	0.06	0.68	1.66	2.41	11.75	18.15
3	0.12	1.38	2.00	3.86	13.35	22.62
5	0.34	2.02	3.15	6.12	16.52	27.88
10	1.20	3.65	5.25	9.93	22.22	35.63
20	3.90	7.98	11.48	18.51	28.36	38.71

Table 7: Stress Test Capital Buffers across Ratings as a Percentage of Banking Book Regulatory Capital

All figures are in percent. Banking book regulatory capital is measured with the Internal Rating Based approach. Results are based on 1920-2008 time series of Moody's default rates.

Rating	AAA	AA	A	BBB	BB	B
Maturity	Panel A: Moody's average transition matrix, 1920-2008					
1.0	0.0	29.6	53.9	24.2	63.9	73.8
2.0	3.6	20.9	48.1	30.1	77.8	87.2
3.0	5.2	32.2	44.4	38.7	75.9	95.8
5.0	9.3	31.2	48.1	45.5	75.4	97.0
10.0	32.0	51.9	71.6	66.9	75.1	108.1
20.0	85.2	89.3	117.7	96.5	83.0	107.2
	Panel B: Nickell et al's transition matrices, 1970-1997					
1.0	0.0	57.8	115.9	51.1	67.3	61.1
2.0	3.9	37.8	91.9	57.0	82.0	73.3
3.0	5.6	55.5	80.1	68.6	80.2	79.2
5.0	10.3	51.9	81.6	76.2	79.5	80.1
10.0	34.6	83.6	116.1	113.3	80.0	90.2
20.0	86.6	136.6	186.3	162.3	90.1	93.6
	Panel C: Bangia et al's transition matrices, 1981-1998					
1.0	0.0	57.8	92.8	28.3	74.7	67.3
2.0	3.2	37.8	76.5	37.1	91.3	81.7
3.0	4.8	55.4	68.1	48.7	90.7	94.6
5.0	8.7	52.4	70.7	56.7	90.1	102.8
10.0	31.2	94.6	117.4	91.5	119.6	128.9
20.0	101.2	207.1	256.6	170.5	152.6	140.0

Table 8: Portfolio Losses and Economic Capital based on the Great Depression Scenario

All figures are in percent. Based on 1920-1960 time series of Moody's default rates.

	Portfolio Credit Quality			
	High	Average	Low	Very Low
	Panel A: Moody's average transition matrix, 1920-2008			
Maturity	Worst Case Loss			
1	2.90	5.57	9.11	10.00
2	4.78	8.86	14.64	16.15
3	6.13	11.07	18.11	20.11
5	8.70	14.47	22.59	24.83
10	12.46	18.77	27.90	30.39
20	19.07	24.93	32.79	34.78
	Average Loss			
1	0.33	0.61	0.99	1.14
2	0.67	1.21	1.94	2.23
3	1.03	1.81	2.89	3.29
5	1.80	3.05	4.81	5.42
10	4.02	6.32	9.56	10.57
20	8.75	12.87	18.63	20.33
	Economic Capital			
1	2.56	4.96	8.12	8.86
2	4.10	7.65	12.70	13.92
3	5.10	9.26	15.22	16.82
5	6.90	11.42	17.78	19.41
10	8.44	12.45	18.34	19.82
20	10.31	12.06	14.16	14.45
	Panel B: Nickell et al's transition matrices, 1970-1997			
	Worst Case Loss			
1	2.90	5.57	9.11	10.00
2	4.74	8.81	14.56	16.05
3	6.04	10.96	17.91	19.88
5	8.51	14.19	22.07	24.25
10	11.89	18.01	26.66	29.04
20	17.27	22.79	29.94	31.84
	Average Loss			
1	0.33	0.61	0.99	1.14
2	0.66	1.18	1.90	2.17
3	1.00	1.74	2.77	3.15
5	1.69	2.86	4.46	5.04
10	3.63	5.71	8.55	9.47
20	7.71	11.40	16.46	18.01

Table 8: Continued

Maturity				
	Panel B: Nickell et al's transition matrices, 1970-1997			
	Economic Capital			
1	2.56	4.96	8.12	8.86
2	4.08	7.63	12.66	13.87
3	5.04	9.22	15.14	16.73
5	6.82	11.33	17.61	19.22
10	8.26	12.31	18.11	19.57
20	9.56	11.39	13.49	13.83
	Panel C: Bangia et al's transition matrices, 1981-1998			
	Worst Case Loss			
1	2.90	5.57	9.11	10.00
2	4.91	9.04	14.87	16.38
3	6.46	11.55	18.72	20.74
5	9.27	15.26	23.57	25.84
10	13.97	20.53	29.87	32.43
20	23.97	30.59	39.20	41.24
	Average Loss			
1	0.33	0.61	0.99	1.14
2	0.67	1.19	1.91	2.18
3	1.02	1.77	2.80	3.17
5	1.75	2.93	4.55	5.09
10	3.83	5.91	8.76	9.62
20	8.17	11.82	16.85	18.29
	Economic Capital			
1	2.56	4.96	8.12	8.86
2	4.24	7.85	12.96	14.20
3	5.45	9.78	15.92	17.56
5	7.52	12.33	19.03	20.75
10	10.14	14.62	21.11	22.80
20	15.80	18.77	22.35	22.96

Rating	Portfolio Composition*			
AAA	3.82	2.92	1	0.5
AA	5.9	5	1.54	1.02
A	29.26	13.38	3.7	3.16
BBB	37.92	31.16	16.54	13.2
BB	19.08	32.44	38.06	35.6
B	2.72	11.12	32.36	37.02
CCC	1.3	3.98	6.8	9.5

* Source: Gordy (2000), p. 132, Table 1.

Table 9: Stress Test Capital Buffers across Portfolios as a Percentage of Banking Book Regulatory Capital

All figures are in percent. Banking book regulatory capital is measured with the Internal Rating Based approach. Results are based on 1920-1960 time series of Moody's default rates.

	Portfolio Credit Quality			
	High	Average	Low	Very Low
Maturity	Panel A: Moody's average transition matrix, 1920-2008			
1	39.4	50.2	56.8	57.1
2	51.9	67.0	79.3	80.7
3	54.9	71.5	86.1	88.9
5	57.4	71.5	84.9	87.6
10	69.6	76.9	86.2	87.9
20	85.0	74.6	66.6	64.1
	Panel B: Nickell et al's transition matrices, 1970-1997			
1	52.6	55.6	55.0	54.3
2	68.2	74.3	77.3	77.3
3	71.3	79.6	84.5	85.7
5	73.8	79.8	84.0	85.0
10	88.5	85.5	85.0	85.2
20	102.4	79.2	63.3	60.2
	Panel C: Bangia et al's transition matrices, 1981-1998			
1	46.3	54.5	57.5	56.9
2	62.3	74.4	82.2	82.4
3	67.6	81.6	91.6	93.2
5	71.4	83.2	92.7	94.3
10	95.4	97.3	101.2	101.9
20	148.6	124.9	107.1	102.6

Table 10: Incremental Credit Risk in Trading Book Capital Requirements: the IRC

Sample period: 7/5/2004-21/08/2009. PIT and TTC stand for "point-in-time" and "through-the-cycle" respectively.

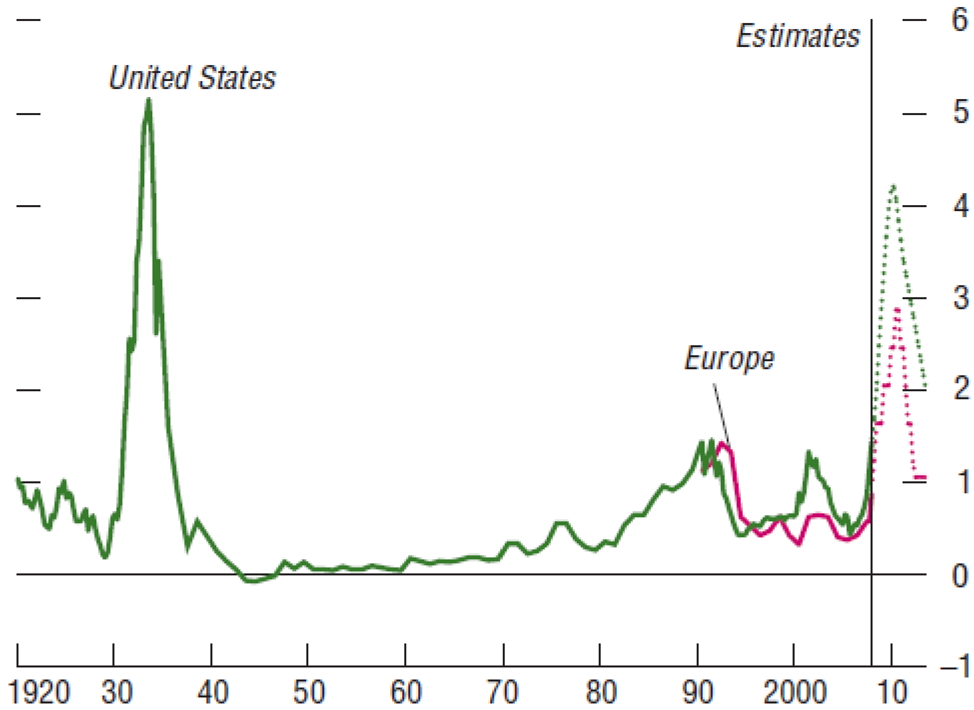
	Bond Indices					
	AAA-AA			A-BBB		
	5-10y	**10-15y**	**15+y**	**5-10y**	**10-15y**	**15+y**
	Industrials, %					
Pre-crisis VaR*	5.48	6.31	9.82	5.01	6.44	9.28
Stressed VaR	17.25	22.13	26.30	17.20	18.87	22.23
Specific Risk**	1.60	1.60	1.60	1.60	1.60	1.60
	3 Month Liquidity Horizon and TTC Ratings					
IRC	1.53	2.54	3.53	4.76	6.56	8.15
Total New Capital	25.86	32.59	41.24	28.57	33.46	41.26
New/Old Capital	3.65	4.12	3.61	4.32	4.16	3.79
IRC/Old Capital	0.22	0.32	0.31	0.72	0.82	0.75
	3 Month Liquidity Horizon and PIT Ratings					
IRC	0.96	1.73	2.55	3.82	5.41	6.82
Total New Capital	25.29	31.78	40.26	27.63	32.31	39.93
New/Old Capital	3.57	4.02	3.53	4.18	4.02	3.67
IRC/Old Capital	0.14	0.22	0.22	0.58	0.67	0.63
	Financials, %					
Pre-crisis VaR*	5.43	7.76	9.57	5.39	6.50	8.61
Stressed VaR	34.18	35.12	39.00	34.80	27.10	31.61
Specific Risk**	1.60	1.60	1.60	1.60	1.60	1.60
	3 Month Liquidity Horizon and TTC Ratings					
IRC	1.53	2.54	3.53	4.76	6.56	8.15
Total New Capital	42.75	47.03	53.70	46.55	41.76	49.97
New/Old Capital	6.08	5.02	4.81	6.66	5.15	4.90
IRC/Old Capital	0.22	0.27	0.32	0.68	0.81	0.80
	3 Month Liquidity Horizon and PIT Ratings					
IRC	0.96	1.73	2.55	3.82	5.41	6.82
Total New Capital	42.17	46.22	52.72	45.61	40.62	48.64
New/Old Capital	6.00	4.94	4.72	6.53	5.01	4.76
IRC/Old Capital	0.14	0.19	0.23	0.55	0.67	0.67

*Computed with data up to 20th June 2007.
**We assume that bank has a model to account for specific risk and this equals the capital charge under the standardised approach. Banks that have an internal model for specific risk will also be subject to the IRC (see BCBS 2009b, p. 2)

Figure 1

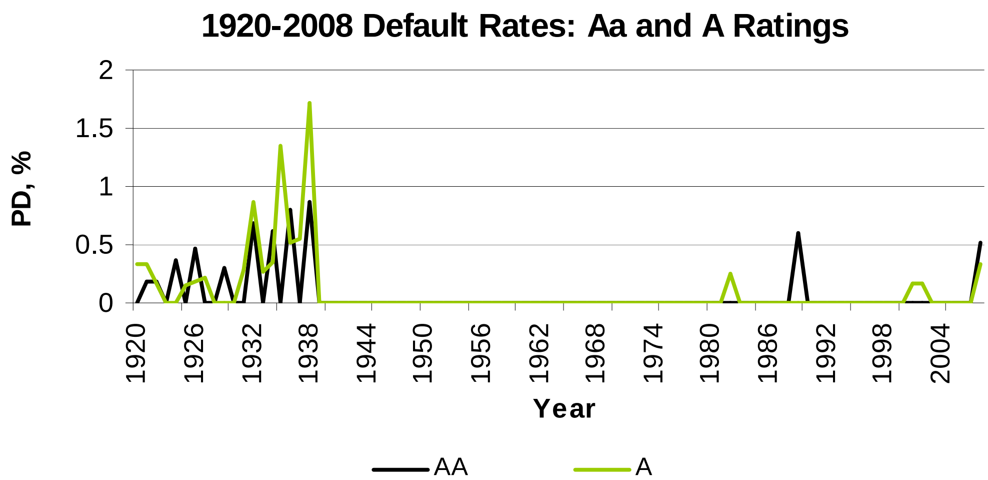
Commercial Bank Loan Charge-Offs

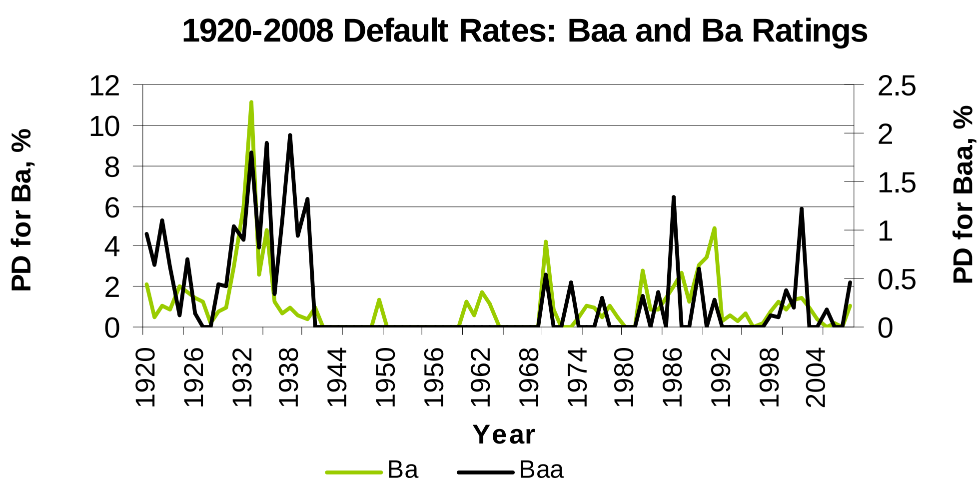
(percent of total loans)



Source: IMF (2009), p. 38.

Figure 2


1920-2008 Default Rates: Aa and A Ratings
PD, %
Year
AA
A


1920-2008 Default Rates: Baa and Ba Ratings
PD for Ba, %
PD for Baa, %
Year
Ba
Baa

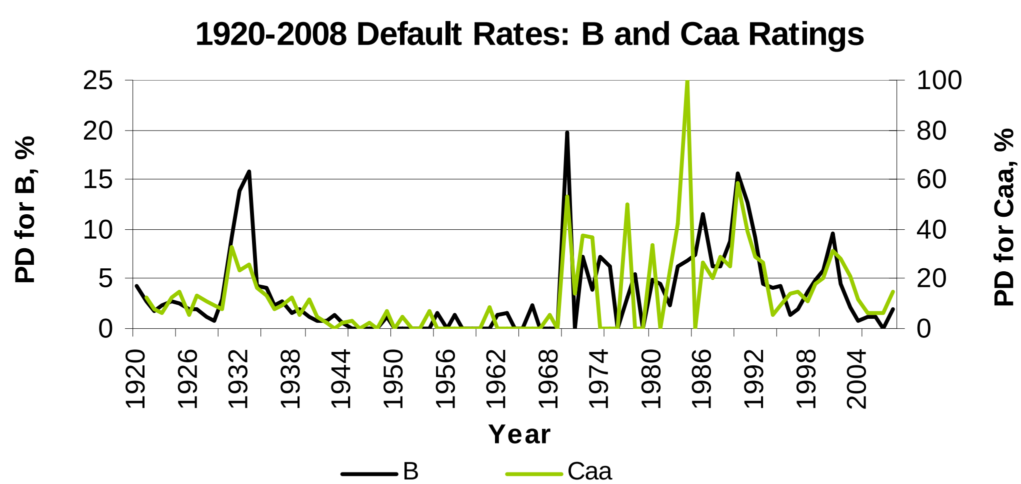

1920-2008 Default Rates: B and Caa Ratings
PD for B, %
PD for Caa, %
Year
B
Caa

Figure 3

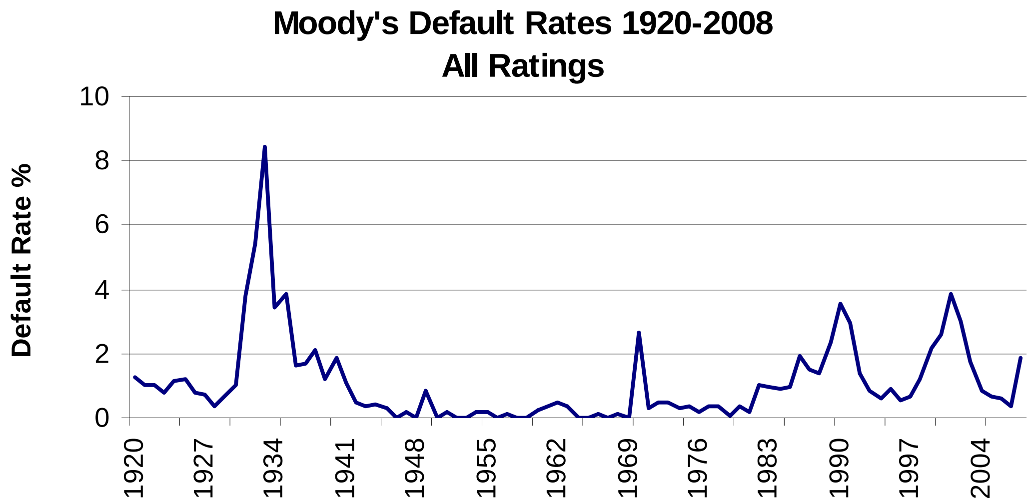
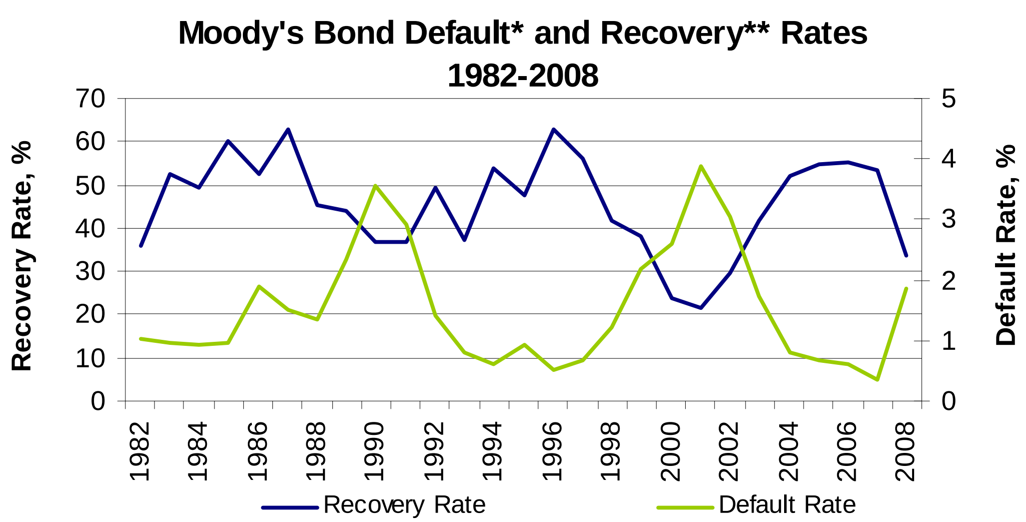


Figure 4



*All ratings, ** Senior Unsecured.

Figure 5

Average and Worst Case Credit Spreads

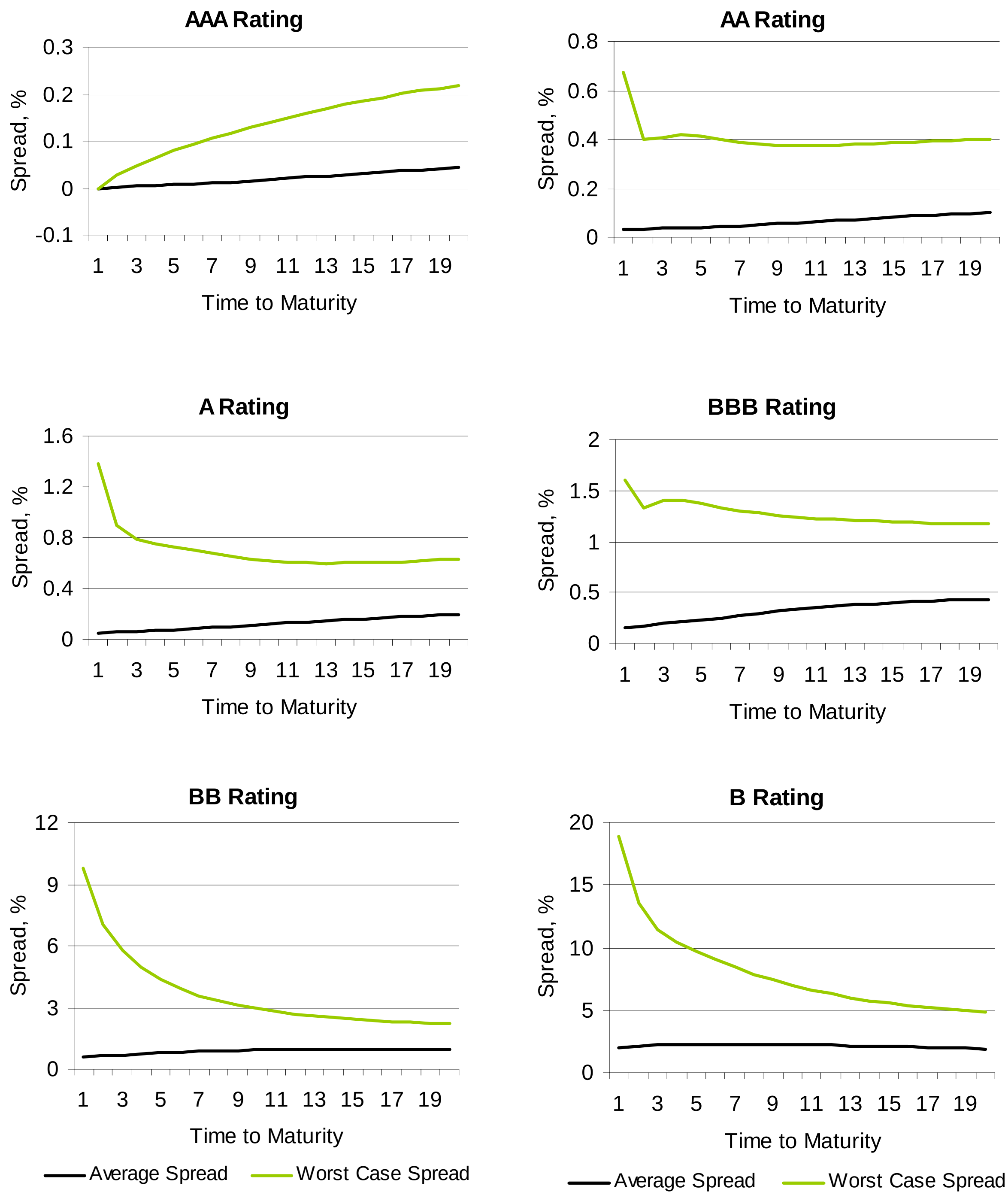


Figure 6

Counter-Cyclical Capital Buffers

5-Year Maturity Bond Exposures