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“Stress Testing Credit Risk: The Great Depression Scenario“

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Abstract

By employing Moody's corporate default and rating transition data spanning the last 90 years we explore how much capital banks should hold against their corporate loan portfolios to withstand historical stress scenarios. Specifically, we shall focus on the worst case scenario over the observation period, the Great Depression. We find that migration risk and the length of the investment horizon are critical factors when determining bank capital needs in a crisis. We show that capital may need to rise more than three times when the horizon is increased from one year, as required by current and proposed regulation, to three years. Increases are still important but of a lower magnitude when migration risk is introduced in the analysis. Further, we find that the new bank capital requirements under the so called Basel 3 agreement would enable banks to absorb Great Depression style losses. But, such losses would dent regulatory capital considerably and far beyond the capital buffers that have been proposed to ensure that banks survive crisis periods without government support.

Keywords: Credit Risk, Financial Crisis, Stress Testing, Basel 3.

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

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1. Introduction

The financial crisis that began in 2007 has 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. Acharya, Philippon, Richardson and Roubini (2009) point out that capital markets before the crisis were characterised by a fundamental mispricing of risk as “risk premiums were too low and long-term volatility reflected a false belief that future short-term volatility would stay at its current low levels”. As a result, regulators have recently re-emphasized the need to couple standard risk measurement tools with stress tests designed to capture crisis scenarios.[3] These should be severe but plausible. 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. 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. Historical stress tests are incorporated in current and proposed regulations of bank capital.[4] Among the main advantages of historical scenarios are the fact that they are plausible, if only because they have occurred before, and are not as sensitive to model risk as hypothetical scenarios. Their main limitation is that often the history of relevant events 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.

[2] See, for example, JPMorgan/Reuters (1996).
[3] See, Basel Committee on Banking Supervision (2009a,b,c), Committee of European Banking Supervisors (2009) and Financial Services Authority (2009).
[4] Nout Wellink, former chairman of the Basel Committee on Banking Supervision recently stated that “[a]ny analysis of appropriate minimum [capital] levels must recognise that to be credible they need to cover historically severe losses”. See Wellink (2010), p. 5.

Indeed the sheer abnormality of the recent crisis - when analysed within the context of short term pre-crisis indicators - becomes far more plausible when put into a longer historical context. Similarly, Giesecke, Longstaff, Schaefer and Strebulaev (2009) conclude that "in coming to grips with the current financial market situation which has been termed a 'historic crisis' or 'the worst financial crisis since the Great Depression,' nothing is so valuable as actually having a long-term historical perspective."

In this study, we estimate credit losses for (1) individual corporate exposures of different credit quality and (2) 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 default and rating transition data, which is the longest on record 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 experience in the 1930s. In addition, according to Moody's, the 2009 aggregate default rate at 5.36% was the third worst since the record began in 1920, behind 1933 (8.42%) and 1932 (5.43%). More remarkably, the default rate of speculative grade assets in 2009 was 12.97% of total issuers, second only to that observed in 1933 (15.39%). As a result, anecdotal evidence suggests that the Great Depression as a central stress scenario may be gaining popularity in the industry[5].

The Basel Committee has recently issued a consultative document (Basel Committee on Banking Supervision (BCBS), 2009c) that highlights principles for sound stress testing in the attempt to address the shortcomings of pre-crisis 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) underestimation of correlation across and within asset classes, (3) system-wide interactions (i.e. systemic risk) and feedback effects were largely ignored. Considering the Great Depression

[5] 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.

scenario allows us to address these concerns in that: (i) The Depression was both severe 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 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 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 regulation; (2) we investigate the loss experience under stress for representative bank portfolios with different credit profiles; (3) we derive counter-cyclical capital buffers based on the Great Depression scenario and illustrate their behaviour over the 1921-2009 sample period; and (4) we compare our stress test estimates of credit risk capital with Basel 2 and Basel 3 regulation.

Historical stress scenarios have recently been proposed to quantify the capital buffers that would help banks to withstand a severe financial crisis (Financial Services Authority, 2009 and Committee of European Banking Supervisors (CEBS), 2009). Risk sensitive capital requirements tend to decrease in booms when risk falls (or is under-estimated) and increase in recessions. In recessions, banks also face higher losses which may erode existing capital reserves. This, combined with higher capital requirements, may lead to a capital shortage. As a result, banks may be forced to cut down on lending in a downturn, thus causing or exacerbating a credit crunch.[6] This pro-cyclical effect of risk sensitive regulatory capital[7] has led researchers to investigate how banks manage the buffer that they normally keep in excess of the regulatory minimum. If banks built buffers in boom

[6] "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).

[7] There is an extensive literature on the pro-cyclicality of risk sensitive regulation. See, for example, 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).

periods and decreased them in recessions then the pro-cyclicality of capital requirements could be partially or completely offset. This, in turn, would help to reduce the potential impact of capital regulation on the length and severity of recessions. Evidence in the literature about the relationship between capital buffers and the business cycle is mixed. Fonseca et al (2010) find that buffers are cycle-neutral in 58 of the 70 countries they have analysed. However, they are pro-cyclical (i.e. there is a significant negative relationship between buffers and GDP growth) in 7 countries including the US and the UK, and counter-cyclical in the remaining 5 countries. Ayuso et al (2004) find that for a large sample of Spanish banks, capital buffers are adjusted in a pro-cyclical fashion and Jokipii and Milne (2008) observe that buffers behave pro-cyclically in EU15 countries and in commercial, saving and large banks while in EU accession countries and small and cooperative banks they are counter-cyclical. To contrast the pro-cyclicality of minimum regulatory capital and, often, of unregulated buffers, Basel 3 has introduced the additional requirement of counter-cyclical buffers.[8] In this paper, we determine the counter-cyclical buffers that would protect banks from Great Depression style losses and show to what extent Basel 3 buffers should be adjusted to provide the same level of protection.

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 Basel regulation, (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 recent 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[9] 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

[8] Specifically, Basel 3 introduces a "conservation" buffer and a "counter-cyclical" buffer. However, both are designed to behave in a counter-cyclical way.
[9] See Foglia (2008) for a comprehensive survey of the macro credit risk models adopted by several national authorities.

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.

Corporate debt defaults have increased substantially during the recent crisis and led to such high profile cases as Lehman, GMAC, Washington Mutual in the financial sector and General Motors, Ford, Lyondell and Charter Communications among non financials. Small and medium enterprises also suffered.[10] Given the substantial exposure of banks to the corporate sector,[11] it is important to investigate how much capital they should hold against their corporate loan book in order to survive crisis scenarios. When deriving adequate capital levels, we find that two critical factors are the holding period assumption and migration risk. The holding period in current and proposed regulation, and in popular credit risk models used in the industry, is set at one year. This implies that, in a crisis, banks would be able to stop losses or recapitalize within that time frame. Empirical evidence, however, suggests that this may be too optimistic. We show that stretching the holding period to 3 years may cause losses, and hence the capital needed to absorb them, to go up by three times. If migration risk is also included in the analysis, losses may rise further by a smaller but still significant amount. We find that Basel 2 regulatory capital would be sufficient to protect banks against Great Depression style losses for high quality portfolios or when the bank is able to recapitalise quickly. But, if recapitalization is impaired and the holding period prolonged beyond one year, low quality portfolios may lead to losses in excess of the minimum capital requirements. The proposed Basel 3 rules, which include additional buffers on top of Basel 2 requirements, lead to capital levels that would absorb Great Depression losses for extended holding periods and across the portfolios considered. However, in many cases, the buffers would be depleted and minimum requirements seriously breached. This suggests that government intervention would still be needed if such severe stress scenario was to represent itself.

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[10] For example, in the heat of the crisis a loan guarantee scheme offered by the UK government to small and medium enterprises experienced a default rate of 28%. (in "UK unveils support plan for small businesses," Financial Times, January 12, 2009).
[11] In 2009 the IMF reported that corporate loan exposures accounted for 15%, 49%, 43% and 27% of total bank loan exposures in the US, UK, Europe and Asia respectively (IMF 2009, Table 1.13, p. 69).

One may object that the costs associated with endowing financial institutions with sufficient capital to absorb Great Depression style losses and still have enough left to operate normally may prove too high. However, Kashyap et al (2010) show that an increase in capital requirements by 10% of risk weighted assets, which would more than double current regulatory levels, would only lead to a modest rise in loan rates. In a recent study involving several competing macro-economic models, the Basel Committee (2010b) find that higher capital requirements would, in the long term, produce a net increase in GDP owing to a lower probability of banking crisis and of their associated costs. They conclude that, over and above the new higher capital charges, and while taking into account the resulting increase in the cost of borrowing, capital and liquidity requirements could be tightened considerably while still generating net gains. Admati et al (2010) echo these findings and conclude that "setting equity requirements significantly higher than the levels currently proposed [under Basel 3] would entail large social benefits and minimal, if any, social costs". Significantly higher capital would hardly be a revolution by historical standards as, in the not so distant past, banks used to be much less leveraged (Berger et al 1995 and Alessandri et al 2009).

The paper is organised as follows. In Section 2 we introduce the model employed to estimate credit losses under historical stress scenarios. In Section 3 we compare our worst case capital measures with Basel 2 and Basel 3 regulatory capital requirements. The data are described in Section 4. In Section 5 we discuss our results as well as tests on the robustness of our findings to alternative recovery rate assumptions and to temporal changes in credit rating standards. Section 6 concludes the paper.

2. The model

Regulatory capital for a buy and hold corporate exposure under the internal rating based (IRB) approach in Basel 2 is defined as the exposure's "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. With the model presented in this Section a new measure of capital is derived in a similar manner. Specifically, our stress scenario is the worst case loss experienced in the 89 years of our sample period. Then, we define "*worst case"* capital as the difference between the worst case loss and the sample average loss.

To derive worst case and average loss we shall take the point of view of a buy and hold investor who keeps his positions until maturity. This is contrary to standard practice in credit risk modelling where value-at-risk measures are typically based on a 1-year holding period, regardless of the maturity of the underlying exposures. The idea is that it will take one year for a bank to close its non-performing exposures and stop losses, or to raise new capital to meet further losses. We maintain that this may not be the case in a crisis and that in a severe downturn banks may be exposed to losses - and may not be able to adequately recapitalize - over longer horizons. In such cases a buy and hold paradigm combined with investment horizons extending beyond 1 year may be more appropriate. Barakova and Carey (2002) for example, in a study of the speed of recovery of troubled US banks, suggest that, in a crisis, a bank may hold on to its non-performing assets in order to prevent spoiling its relationship with existing customers and to avoid the decline in franchise value that may result.[12] Furthermore, they note that in response to stress conditions, portfolio rebalancing (e.g. by withdrawing lending to customers in trouble) is not a predominant strategy and that recapitalization programs, consisting mostly of new share issues and retained earnings, are preferred. Similarly, Caballero et al (2008) argue that in Japan, during the "lost decade" following the burst of the asset price bubble in the early '90s, banks were hard pressed not to write off non-performing loans, and to roll over those that were about to mature, for three reasons: (1) to avoid breaching minimum capital requirements that would have followed had losses been recognised, (2) to prevent criticism from the public that banks were making the recession worse by denying credit to corporations and, (3) to meet demands from the government to lend to small and medium enterprises, the worst hit by the credit crunch. This behaviour, called forbearance lending (or, alternatively, zombie or evergreen lending), is also described by Krugman (1998) who observes that banks that suffer losses following a crisis may have the incentive to undertake risky projects in a "gamble for resurrection" which, besides Japan,

[12] On a similar vein, during the recent crisis several banks, including Citigroup, HSBC, Société Generale, Rabobank and Standard Chartered, in order to preserve their reputation, brought back on their balance sheet the exposures of structure purpose vehicles (SIVs) that they had established as off-balance sheet entities in connection with securitization programs (CEBS 2009, p.1).

was also witnessed in the US during the Savings and Loans crisis of the '80s. One may argue that although losses may not be stopped within one year, banks can always cover them by raising new equity or with retained earnings. However, Barakova and Carey (2002) show that "several years frequently elapse between the onset of distress [due to large credit losses] and recapitalization". This is because a troubled bank may find it difficult to convince investors to subscribe new equity issues in the aftermath of a crisis. The authors find that all the large banks in their sample recover from a crisis within 2 to 5 years, depending on the distress measure used to define recovery, while smaller banks may take longer.

Although we shall focus on bank capital needs under stress for individual loans and loan portfolios, for simplicity we assume that the exposures in our analysis have the cash flow structure of plain vanilla corporate bonds. Default losses (average and worst case) are estimated by employing default and transition histories from Moody's Investors Service which are obtained from a combined sample of corporate bonds and bank loans. This is consistent with current regulation that allows banks to employ historical default data from rating agencies to measure the expected default loss for corporate loans.[13]

Similarly to Elton et al (2001) we compute the value V_τ of a corporate exposure at a given time τ with the following iterative equation,

$$V_t = \frac{aP_{\tau,t+1} + \left(C + V_{t+1}\right)\left(1 - P_{\tau,t+1}\right)}{1 + f_{t,1}} \quad \text{for } t = \tau, \tau+1, \ldots, \tau+n-1 \qquad (1)$$

where C is the interest charge, n the time to maturity in years, a is the recovery rate, $P_{\tau,t}$ is the probability of default in period t conditional on no bankruptcy in the τ to t period, $f_{t,1}$ is the one-year zero-coupon risk free forward rate at time t, and $V_{\tau+n}$ is the par value of the exposure which is set to 1. The numerator of (1) is simply the expected value of the

[13] "Banks may associate or map their internal grades to the scale used by an external credit assessment institution [i.e. a rating agency] or similar institution and then attribute the default rate observed for the external institution's grades to the bank's grades." (BCBS 2006, p. 102, paragraph 462).

exposure at time $t+1$. This is given by the value of the exposure in the non-default state $(C+V_{t+1})$ multiplied by the survival probability $(1-P_{\tau,t+1})$ plus the value of the exposure in the default state, which equals its recovery value $aV_{\tau+n}=a$, multiplied by the default probability $P_{\tau,t+1}$. The equation is solved backward from $t=\tau+n-1$ to arrive at the price at the date of interest $t=\tau$.

The default probabilities employed in (1) are not risk neutral but "physical" unlike in conventional risk neutral pricing. Risk neutral default probabilities are higher than physical ones because they include a risk premium that takes into account compensation for risk as well as other factors that normally influence credit spreads. Elton et al (2001) use the risk neutral valuation framework with physical default probabilities in order to isolate the expected default loss component from credit spreads. This way, the risk premium is filtered out. Not considering the risk premium when deriving credit losses is consistent with our hold to maturity assumption. This is because if the investor is not expected to liquidate his holdings before expiry he will not face the cost of discounting them at prevailing market rates. By holding an asset to maturity one will only incur a cost if the issuer defaults and such cost is accurately captured by the expected default loss computed with physical default probabilities. These are typically proxied with historical default rates. Historical default rates are commonly used in the literature to measure credit risk losses in banks (see, for example, Carey, 2002, Perli and Nayda, 2004, and Jacobson et al, 2006). Below we show that our definition of credit loss is consistent with that adopted by rating agencies.

We define the expected default loss L_τ at time τ for a corporate exposure with price V_τ as,

$$L_\tau = \frac{G-V_\tau}{G} = 1-\frac{V_\tau}{G} \tag{2}$$

where G is the price of a risk free asset with the same cash flows as the corporate exposure. G represents the present value of contractual cash flows in the absence of default risk, while V is the expected present value of the same cash flows in the presence of default risk. Then, L can be interpreted as the percentage (expected) fall in cash flow due to default risk. For example, if the corporate exposure is a pure discount loan with maturity in 1 year and par value of 1, then $G = (1 + f_{\tau,1})^{-1}$ and $V_\tau = (1 - (1-a)P_{\tau,\tau+1})(1 + f_{\tau,1})^{-1}$. Our loss definition would yield $L_\tau = (1-a)P_{\tau,\tau+1}$ which is the familiar product of the loss given default $(1-a)$ and the 1 year probability of default for the corporate exposure of interest. This is consistent, for example, with the loss definition adopted by Moody's (Moody's 2009, p. 54). For periods over one year, however, Moody's employ an approximation. They define the expected credit loss of an exposure with maturity T as the product of the average cumulative default rate over T periods and the average loss given default over the same period. Our approach is a refinement of Moody's method in that (1) we use the whole term structure of default rates, rather than relying on average cumulative default rates and (2) we differentiate among exposures with different contractual cash flows.

Then, the worst case and average default loss, L_W and L_A, for a buy-and-hold investor and a given exposure, can be defined as, respectively, the maximum and average default loss, computed over a defined stress testing period $\tau \subset (\omega_1, \omega_2)$,

$$L_W = \underset{\tau}{Max}\left(L_\tau \middle| a = a_W\right) = 1 - \frac{\underset{\tau}{Min}\left(V_\tau \middle| a = a_W\right)}{G} = 1 - \frac{V_W}{G} \tag{3}$$

$$L_A = \underset{\tau}{Average}\left(L_\tau \middle| a = a_A\right) = 1 - \frac{\underset{\tau}{Average}\left(V_\tau \middle| a = a_A\right)}{G} = 1 - \frac{V_A}{G} \tag{4}$$

where a_W and a_A are the worst case and average recovery rate respectively. So, our definition of "worst case capital" K_W as a percentage of G will be,

$$\frac{K_W}{G} = L_W - L_A = \frac{V_A - V_W}{G} \tag{5}$$

The difference $V_A - V_W$ is reminiscent of a value-at-risk measure commonly defined as the difference between the mean and a pre-defined quantile of the distribution of exposure values. Here, instead of a quantile we employ the worst case loss over the sample period. To implement pricing equation (1) we need to derive the conditional default probabilities $P_{\tau,t}$.[14] These can be computed from cumulative default probabilities $CP_{\tau,t}$. $P_{\tau,t}$ is the ratio of the unconditional probability of default in period *t*, given by $(CP_{\tau,t} - CP_{\tau,t-1})$, and the probability of no default in an earlier period, which is $(1 - CP_{\tau,t-1})$.[15] Note that for *t* equal to $\tau + 1$, $P_{\tau,\tau+1} = CP_{\tau,\tau+1}$. The next step is the estimation of the cumulative default probabilities. These are influenced by annual default probabilities and rating migration risk. Migration risk can be accounted for through the use of rating transition matrices. Specifically, $CP_{\tau,t}$ can be obtained from the default column of a transition matrix $M_{\tau,t}$ that spans a period of $t - \tau$ years from time τ. Under the *heterogeneous* Markov chain assumption, $M_{\tau,t}$ results from the product of one-year transition matrices estimated between τ and *t.* In this we depart from Elton et al (2001) in that they obtain cumulative default rates with the *homogeneous* Markov chain assumption, which imposes that annual transition matrices remain constant 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 annual transitions time varying. The assumption of time heterogeneity is employed, for example, in CreditPortfolioView, a credit risk model proposed by McKinsey consulting.[16] Bluhm and Overbeck (2007) show how heterogeneous Markov chains can be successfully used to fit the term structure of default rates.

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[14] Note that the subscripts τ and *t* of the probability $P_{\tau,t}$ are two time indicators and hence the probability can be conditional or unconditional with respect to both. The subscript τ relates to time over the sample period, while *t* relates to time over the life of the exposure when the cash flows occur.
[15] For more details on this see Hull (2006), p. 482.
[16] See Crouhy et al 2000, equation 40.

2.1 Default loss sensitivity to interest rates

The worst case or average default losses in (3) and (4) depend on the ratio V/G. And both, the price V of the corporate exposure and the price G of the riskless asset, depend on interest rates. Since, by construction, the corporate exposure and the riskless asset have the same cash flows, the sensitivity of the riskless asset to interest rates, that is, its duration, is necessarily higher. 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/G also increases because G will fall more than V. As a result, the default loss $1-V/G$ 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) IRB regulatory capital is derived with the implicit assumption of zero interest rates. Then, setting interest rates to zero allows us to compare worst case capital and regulatory capital in terms of their implied levels of credit risk alone, that is without interest rate effects. However, we have measured the impact of different interest rate assumptions on our worst case capital estimates and found them to be small (see Results Section).

3. Bank regulation and our model

3.1. Comparability of worst case capital with IRB capital in Basel 2

With the model presented in the previous Section we derive a measure of worst case capital K_W for a given exposure as the difference between the exposure's worst case loss and average loss, $L_W - L_A$. It is easy to show that, for a 1 year exposure, the worst case capital resulting from the model illustrated in Section 2 and the IRB capital, K_{IRB}, are consistent with one another. The details are provided in the Appendix. However, this is not the case for maturities longer than 1 year. This is because worst case capital is derived with a hold to maturity approach, while in the IRB the risk horizon is always 1 year, regardless of the maturity of the exposure.

3.2. Basel 3 capital buffers

Following the subprime crisis the Basel Committee has introduced several changes to the Basel 2 framework, which have been collectively termed Basel 3. The objective of the new measures is to increase the ability of the individual bank, and the banking industry as a whole, to absorb losses in a crisis. This, in turn, would be instrumental in reducing the likelihood of negative spillovers from the financial sector to the real economy and the necessity of government bailouts with the consequent possible exposure of taxpayers to large losses (BCBS 2009b, p. 1-2). The Basel 3 provisions include (1) higher "quality, consistency and transparency of the capital base" (2) a limit on leverage (3) new liquidity standards and (4) capital buffers[17] over and above minimum capital requirement designed to absorb losses in a crisis while preserving the regulatory minimum. In this paper, we shall focus on the last measure. The buffers will have a cumulative value of 5% of risk weighted assets. When credit risk capital is estimated with the IRB, risk weighted assets are given by 12.5 times K_{IRB}. So, the buffers are given by 0.05x12.5xK_{IRB}. With our historical default and migration data and our model we shall explore whether the cumulative buffer will be sufficient to cover for losses in the crisis scenarios occurred over the last 90 years.

4. The data

To estimate worst case capital we employ annual transition matrices based on all the firms that have issued bonds or loans rated by Moody's in the period 1921-2009. The sample is dominated by US companies that represent an annual average, over the observation period, of 85% of all issuers. Default rates for all broad rating categories, which are obtained from the last column of the annual transition matrices, are shown in Figure 1. For all, except the lowest two categories, B and Caa-C, the highest default

[17] For more details on the Basel 3 measures and capital buffers see for example Basel Committee (2009b and 2010a) and Cecchetti (2010).

frequency occurred during the Great Depression. The default rates of B and Caa-C assets are highly volatile during the 1970s and 1980s and reach their highest peak in that period. However, the number of B and Caa-C 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 1.4, 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 1 shows 1 to 10 year cumulative default rates obtained from 1 year aggregate default rates. The Great Depression period consistently features as the most severe scenario.

Worst case capital over investment horizons longer than 1 year are influenced by default rates as well as migration rates. An asset that migrates to a lower (higher) rating in a particular year will have a higher (lower) risk of default in the following years. Since in our analysis we consider investment horizons beyond 1 year it is important to take into account the whole of the transition matrix when deriving default losses. Examples of annual transition matrices estimated over different time periods are shown in Table 2. The first column of a matrix indicates the initial rating at the beginning of the year and the first row denotes the final rating (or default) at the end of the year. The Table shows that transition matrices vary considerably over time. As we shall see, this results in markedly variable loss patterns during the sample period. In Panel A we report the average transition matrix over the whole sample from 1921 to 2009. This can be used as a benchmark to compare against stress transition matrices estimated in periods of turbulence, such as, the "Great Recession" (2008-2009) and the Great Depression (1931-1935) shown in Panel B and C respectively. The 1931-1935 interval was chosen to characterise the Great Depression because it exhibits abnormally high default rates (greater than one standard deviation above the long term mean) on each year in the interval. However, even within the 1931-1935 period, variability is significant. In panel D we report the transition matrix estimated in 1932 which shows, almost invariably, far larger default rates and migrations rates than the average Great Depression matrix. Below each matrix we show a mobility indicator. This is a simple way to summarise the extent of migration and default risk across all ratings for a given matrix. Intuitively, the higher the rates in the main diagonal of a matrix, which denote the frequency with which ratings remain unchanged, the lower the variability of the ratings over time. Then, in a matrix with N ratings, N minus the trace of the matrix, that is, the sum of all the its diagonal elements, provides a good summary of its overall variability or “mobility”. The mobility indicator employed in Table 2 was developed by Jafry and Schuermann (2004). Their measure is a refinement of, and indeed often very close to, the trace based indicator. As one should expect, the 1921-2009 average matrix has the lowest mobility (11.68%). The Great Recession matrix has a mobility almost twice as large (20.95%). The Great Depression average matrix is still more volatile with a mobility of 25.51% which almost doubles if we consider the year 1932 alone (44.47%). Remarkably, from the 1921-2009 average to the 1932 worst case scenario, mobility increases four-fold.

Mobility and default rates are very highly correlated (see Figure 2). But there are exceptions. In the late ‘30s and early ‘80s mobility increased sharply without a corresponding rise in default rates even though, as shown in Figure 3, those periods were characterised by a recession (as defined by the National Bureau of Economic Research). This suggests that the impact of those recessions on credit risk resulted mostly in higher migration rates. Interestingly, the level of mobility in 2009, following the sub-prime crisis, is comparable with the peak immediately after the Great Depression (1938) and the recessions in the ‘80s and ‘90s.

4.1 Recovery rates

Worst case and average loss in (3) and (4) depend on the assumed value for the worst case and average recovery rate respectively. Structural-form credit risk models imply that recoveries should be low in periods characterised by high default rates.[18] Altman et al (2005) find that bond speculative grade default rates can explain a substantial portion of the volatility of bond recovery rates. The authors suggest that the negative relationship between the two variables are caused by the excessive supply of defaulted securities in

[18] See Altman (2009) for a review of the literature and Bruche and Gonzalez-Aguado (2010) for a recent study on the implications for risk management of the negative relationship between recovery and default rates.

high default periods which causes post default prices, a standard measure of recovery value in the bond market, to fall. Araten et al (2004) also find a negative and statistically significant relationship between default rates and recoveries for bank loans in a 18 year study that covers the 1982-1999 period. Recent evidence by Moody's indicates that recovery rates increase in an economic upturn and decrease in a downturn (Emery 2008). In Table 3 we summarise worst case and average bank loan recoveries in the available literature.[19] Results are broadly consistent and show a minimum recovery ranging from 46.5% to 53.4% and an average recovery from 63.1% to 69.7%. In our study, we shall adopt as a benchmark the downturn and average recoveries that were employed by Moody's to make predictions on expected credit losses during the recent crisis related to debtors with only bank loans outstanding.[20] These are 50% and 65% respectively (see Emery 2008, footnote 16). These recoveries were derived under the assumption of a "stress downturn" that would produce worst case recoveries 10% below the average observed in the previous US recessions of 1990-1992 and 2000-2002. It appears that a recovery rate contraction of this order of magnitude looks plausible also in the context of the Great Depression. Based on a study of the bond market during the 1900-1943 period, Hickman (1960), as part of a comprehensive corporate bond research project prepared for the National Bureau of Economic Research, recorded prices at default of a large sample of US bond issues. Although bond recoveries are typically lower than loan recoveries and cannot be used as a proxy for the latter,[21] they can reasonably be employed to form a broad view on recovery patterns. In Figure 4, we report bond recoveries during the Great Depression derived with Hickman's bond data. The 1931-33 average recovery is 21.7% which is 8.9% below the average bond recovery (30.6%) during the 1990-92 and 2000-02

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[19] The Table shows ultimate recoveries, that is recoveries obtained by discounting to the default date all the cash and/or securities, net of bankruptcy costs, received by creditors until the end of the bankruptcy period. For a discussion of alternative recovery calculation methods see, for example, Calabrese and Zenga (2010).

[20] Assuming that the debt of a corporation is made by bank loans alone is certainly plausible for small and medium enterprises. However, during a crisis, it may also be a plausible - although conservative - assumption even in the case of large corporates. Normally, large firms may have debt which is junior to bank loans (e.g. unsecured bonds) which will influence loan recovery rates. However, the Great Recession of 2008-2009 highlighted that, during serious crises, probably due to favourable pre-crisis lending conditions, the proportion of loan-only borrowers may be substantial even among large corporations. In 2008 Moody's reports that "The rapid growth of issuers having only rated loans and no bonds outstanding (i.e., "loan-only issuers") has played a substantial role in increasing loans' share of total debt across Moody's-rated issuers. US loan-only issuers now comprise almost 60% of all US issuers that have rated loans and 34% of all US speculative-grade rated issuers." (Emery, 2008).

[21] Bond recoveries are typically lower than loan recoveries because bonds normally rank lower than loans in the seniority structure of a firm's debt.

recessions. This is remarkably close to the 10% drop in stressed downturn recoveries for bank loans assumed by Emery (2008).

The recovery data in Hickman (1960) are based on the US experience in the first half of the twentieth century. However, the legal and institutional environment that were prevalent in the US at that time, which have no doubt affected recoveries, have since changed.[22] Also, the US findings may not be representative of other countries. Davydenko and Franks (2008) report that differences in bankruptcy codes cause the distribution of recovery rates to vary substantially across countries. They look at three countries with different legal environment, namely, France, Germany and the UK and find that their average bank loan recoveries for a large sample of small and medium enterprises to be markedly different at 54%, 61% and 74% respectively. To illustrate the effects of legal and other factors that may cause a departure from our benchmark minimum and average recovery values of 50% and 65%, we shall perform a sensitivity analysis on our findings by using alternative recovery assumptions. This analysis is reported in the results Section.

5. Results

In this Section, we present our estimates of worst case capital for individual assets of different credit quality and for stylised bank portfolios. Worst case capital is then compared with Basel I, Basel II and Basel III regulatory capital and Basel III counter-cyclical buffers. The analysis is concluded with tests on the robustness of our findings to alternative recovery rate assumptions and to time variation of credit rating standards.

Worst case loss, average loss and their difference, worst case capital, for individual assets[23] rated from Aaa to single-B and holding periods from 1 to 3 years are shown in

[22] The Great Depression prompted a radical review of the bankruptcy legislation in the US leading to the enactment of the Chandler Act in 1938 which replaced the 1898 Bankruptcy Act (Bradley, 2001).

[23] Similarly to Elton et al (2001), the interest paid on each exposure is determined endogenously for every credit rating. The interest is set to equate the price of a 3 year exposure to its par value. As a robustness check we have used alternative interest assumptions and found only second order effects in our results. Specifically, interest charges were also implicitly determined in order to set to par the price of bonds with maturities of 1 and 2 years.

Table 4. The worst case scenario coincides with the Great Depression in all except single-B rated assets over a 1 year holding period which, as shown in Figure 1.3, recorded the highest default rate in 1970. The Caa-C ratings are dropped for the ratings-based analysis because they exhibit anomalous default rate volatility and abnormally high default rates in the early 1980s, both a likely consequence of small sample problems. Figure 5, which shows Caa-C historical default rates against the number of issuers in this category, supports this conclusion. 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 were 33.3%, 0%, 23.1%, 42.1%, 100%, 0% and 26.7%.

In Table 4 we report our credit losses and worst case capital without (Panel A) and with (Panel B) migration risk in order to determine the incremental effect of its inclusion.[24] As suggested in Carey (2002), we explore cumulative losses over horizons of up to three years. As one may expect, worst case loss, average loss and worst case capital estimated with or without migration risk increase as credit quality declines and as the holding period increases. The only exception is worst case capital derived without migration risk for Aa over 2 years which is lower than for a 1 year horizon as, uncharacteristically, the average loss grows faster than the worst case loss in this case. This is because the worst case Aa losses over one and two years are virtually identical as both are exclusively driven by the default rate in the worst year, the default rates of adjacent years being equally zero.

Worst case and average loss are zero for Aaa assets with a 1 year holding period because no default has ever occurred in the top rating category. When migration risk is ignored,

[24] Migration risk can be excluded by computing cumulative default probabilities (see Section 2) with annual default probabilities only, that is, without considering downgrade and upgrade probabilities. If we denote the annual default probability at time s as $Q_{s,s+1}$ then the cumulative default probability between year τ and t, without migration risk and with the usual (heterogeneous) Markov assumption, will be $CP_{\tau,t} = 1 - \prod_{s=\tau}^{t-1}\left(1 - Q_{s,s+1}\right)$ that is 1 minus the probability of survival over that period.

default via successive downgrades is ruled out. Hence, Aaa credit losses over 2 and 3 years are also zero. On the other hand, the inclusion of migration risk, as shown in Panel B, introduces the possibility of (indirect) default even for Aaa. The incremental impact of migration risk is shown in Panel C. Interestingly, the Baa category exhibits the largest increase in worst case capital by 132% and 139% relative to the no-migration case for the 2 year and 3 year horizons respectively. This means that an investor may need a capital cushion against its credit risk portfolio that is more than two times as large when migration risk is factored in. The result for Baa is particularly significant as this is the median rating category of credit portfolios held by high and average quality banks as reported by Gordy (2000). The holding period is also a critical factor for the size of worst case capital. For example, by extending it from 1 to 3 years, worst case capital for the Baa category more than doubles (+120%) from 0.96% to 2.11%, under the no-migration risk case, and goes up by 424% from 0.96% to 5.05% when migration risk is accounted for.

Results in Table 4 are derived under the assumption of zero interest rates. To see the sensitivity of our estimates to this assumption we have computed the changes in worst case capital (with migration risk) when interest rates are increased to 3% and 6%. Results are reported in Table 5. As discussed in Section 2.1, higher interest rates will cause credit losses to fall. In absolute terms, the worst case loss falls more than the average loss thus producing lower worst case capital levels as interest rates go up. However, the extent of the decline is small. The largest percentage change is for A assets which show a fall in worst case capital by 2.70% and 5.44% when interest rates climb from zero to 3% and 6% respectively. The impact of interest rates at 1 year holding period is always nil as the discount rate cancels out when computing average and worst case losses at that horizon.

To form a view of the extent to which capital requirements under current and proposed regulation will be sufficient to protect banks in a Great Depression scenario we compute the ratios of the estimated worst case capital measures to the capital requirements under Basel 1, Basel 2 and Basel 3. Several countries have migrated or are in the process of migrating to Basel 2 from Basel 1, while Basel 3 will be gradually introduced over a transition period that is scheduled to end in 2019. Basel 1 capital is given by 8% of risk weighted assets, where all corporate exposures are risk weighted at 100% regardless of their rating or maturity. Basel 2 credit risk capital requirements can be computed with a standardised approach or the internal rating based approach[25]. Here, we shall focus on the latter.[26] In Basel 3, qualifying banks can still measure credit risk capital for plain corporate exposures with the IRB approach but with the addition of capital buffers. Ratios of worst case capital to regulatory capital for corporate exposures of different credit quality and maturity are shown in Table 6. It should be noted that maturity indicates both the maturity of the assets and the holding period when we compute worst case capital. However, the holding period is always 1 year regardless of the maturity of the assets as far as regulatory capital under Basel 2 and Basel 3 is concerned.[27] Hence, the ratios in the Table will reflect (1) the difference between our worst case scenario and the downturn scenario embedded in the regulatory requirements and (2) the difference in holding period assumptions. When the ratios exceed 100%, regulatory capital is insufficient to protect the bank against Great Depression style losses. In Panel A we can see that for Basel 1 this is always the case for the two lowest rating categories, across the holding periods considered, except for Ba loans held over a 1 year horizon. For investment grade loans, on the other hand, regulatory capital appears to be always sufficient. The lack of risk sensitivity in Basel 1 is reflected in the steep increase in the ratios as maturity goes up and as credit quality declines. When we look at Basel 2 (Panel B), the ratios also trend upward as the holding period rises and the rating worsens, but in a less pronounced way. This suggests that the higher risk brought about by lower ratings and longer maturity is captured, even though partially, by the new regulation. These results, however, do not necessarily tell us whether, in the Great Depression scenario, a bank regulated under Basel 1 and Basel 2 will deplete all the capital allocated to its loan portfolio. This will depend on how much extra loss-absorbing capital the bank holds in excess of the regulatory minimum. Basel 3 has introduced capital buffers in addition to

[25] 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 worst case capital obtained from our model.

[26] Unlike for worst case capital where recovery rates vary for average loss (65% recovery) and worst case loss (50% 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 the Appendix). So, for the IRB capital we shall use a common 50% recovery.

[27] No specific mention to any holding period assumption is made under Basel 1.

the minimum requirement in Basel 2 in the attempt to regulate the amount of this extra capital. The objective is to make the buffers large enough to ensure that banks will be able to use them to offset losses in a crisis without breaching the regulatory minimum. In panel C we show that the buffers would be Great Depression-proof only for assets of high credit quality. Baa rated loans will generate cumulative losses that exceed the buffers by 26.5% and 49.2% over a period of 2 and 3 years respectively. For lower ratings, however, the buffers will be exhausted and minimum requirements breached even at a 1 year horizon. This implies that although Basel 3 total capital (Panel D) would always be sufficient to meet Great Depression losses, for lower ratings the minimum requirements would be eroded considerably.

In Figure 6 we show the behaviour over time of countercyclical capital buffers under Basel 3 and those implied by the Great Depression scenario.[28] The graphs allow us to see how the buffers would have adjusted to absorb losses resulting from the default and migration rates on record since the early 1920s. Results are shown for a 3 year holding period. At each point in time the Great Depression buffers are the difference between the worst case capital and the cumulated portfolio losses in excess of the average loss over the previous 3 years. Only the current losses in excess of the average loss are considered because the average loss is assumed to be met by the bank through loan loss provisions. Consistently with Table 6 Panel C, the Basel 3 buffers are greater than the Great Depression buffer for Aaa, Aa and single-A assets, while the opposite is true for all the

[28] To derive time dependent capital buffers over the sample period, we need to compute credit losses with time varying recovery rates from 1921 to 2009. However, Moody's provide a time series of recoveries (for 1st lien loans) only from 1990. We have populated the time series of recovery rates between 1921 to 1989 by exploiting the high negative correlation of recovery and default rates between 1990 and 2009 (-48%). We have done so by computing quantiles, at 5% intervals, of the empirical distribution of aggregated default rates (1921-2009) and the distribution of recovery rates (1990-2009). We have then taken each default rate in the 1921-1989 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 1921 default rate is closest to the 25% quantile of the aggregate default rate distribution, we have assumed that the 1921 recovery rate would be the 75% quantile of the empirical distribution of recoveries. We have then adjusted the mean of the obtained series to ensure that its minimum equals 50% to be consistent with our benchmark worst case recovery assumption employed to derive previous results. The resulting mean of the series is 67% which is close to the 65% average recovery benchmark. An alternative procedure would be to extrapolate recoveries for the 1921 to 1989 period on the basis of a regression of recovery rates on default rates in the 1990-2009 period. However, the quantile matching method explained above enables us to capture, better than a simple regression, the low recovery values associated with the Great Depression period which can be inferred from the evidence reported in Hickman (1960) and summarised in Figure 4.

lower rating categories. Interestingly, besides during the Great Depression, losses of single-B assets also exceed the Basel 3 buffers in 1991 and 1992.

We repeat the ratings-based analysis of credit losses and worst case capital 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 7 (Panel D).[29] 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. It should be noted that this procedure allows us to take into account default correlations across ratings since the time series of portfolio losses will reflect the ratings' empirically observed default rates which embed their default dependence structure. 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 Caa 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 worst case capital for all the portfolios considered are computed with Moody's default histories in the 1921-1960 time interval. Although not ideal, this solution still allows us to study losses in the Great Depression period which is the main focus of our study. Results in Table 7 reveal, with some minor exceptions, that worst case loss, average loss and worst case capital of high and average quality portfolios lie between the corresponding measures for Baa and Ba assets reported in Table 4 and that those of low and very low quality portfolios lie between Ba and B

[29] Gordy (2000) originally reported portfolio compositions based on Standard and Poor's ratings. We have assumed, as is common practice, that Moody's and Standard and Poor's main rating categories are broadly consistent and in the Table have reported the corresponding Moody's categories.

assets. This is consistent with the portfolio composition and median rating for each portfolio shown in Panel D of Table 7. The inclusion of migration risk has a significant impact on worst case capital across all portfolios (Panel C). This is due to the sizeable exposure of each portfolio to Baa and/or lower quality assets which, as shown in Table 4, are the most sensitive, in absolute terms, to the inclusion of migration risk. In relative terms, migration risk will cause worst case capital to rise between 68% (high quality portfolio) and 16% (very low quality portfolio) over a three year horizon. Regarding the influence of the holding period, our results show that going from a 1 year to a 3 year horizon, when migration risk is accounted for, will cause worst case capital to rise more than twice, from 5.99% to 13.69%, for a very low quality portfolio and more than three times, from 1.69% to 5.27%, for a high quality portfolio. For portfolios with intermediate quality the variation lies between these two boundaries.

To appreciate the size of the worst case capital estimated for the portfolios considered we reproduce in Table 8 its ratios to Basel 1, Basel 2 and Basel 3 capital. Over a 1 year horizon Basel 1 and 2 appear to be large enough to absorb Great Depression unexpected losses (i.e. in excess of average losses) across all portfolios (Panel A and B). But, over a 2 and 3 year horizon, low and very low quality portfolios will lead to losses above the regulatory minimum. As noted in the ratings-based analysis, the ratios grow less steeply in Basel 2 in almost all cases owing to its higher risk sensitivity. Notably, worst case capital is 62.2% and 77.3% higher than the Basel 1 requirements for low and very low quality portfolios over a three year horizon as opposed to 21.9% and 24.2% higher than the Basel 2 requirements. Remarkably, Basel 3 buffers appear to be too small in all cases considered except the 1 year horizon for the high and average quality portfolios. For instance, for a 3 year holding period, unexpected losses will go beyond the buffers by 75.0% and 95.0% for the average and low quality portfolios. In Figure 8 we report the behaviour of Basel 3 and Great Depression implied countercyclical buffers for a three year horizon over the 1921-1960 sub-sample.

How large should the buffers be in order to provide sufficient cover? To answer this question we compute the implied size of the buffers, as a percentage of risk weighted assets, that would match the unexpected credit losses in the Great Depression period.

Results are shown in Table 9. When a holding period of 3 years is employed, the 5% buffer level imposed by Basel 3 is insufficient in all cases. The buffer should go up substantially to match Great Depression unexpected losses and reach 7.5%, 8.7%, 9.7% and 9.9% for high, average, low and very low quality portfolios respectively.

5.1 Robustness tests on recovery rates

Our results are derived with the assumptions of a worst case and average recovery of 50% and 65% respectively. We test the sensitivity of our findings to these assumptions by deriving worst case capital to Basel capital ratios across portfolios with alternative minimum and average recoveries. In Panel A of Table 10 we report ratios based on a worst case and average recovery of 40% and 55% respectively, that is 10% below the benchmark values employed to derive the main results. The lower recoveries increase worst case capital because worst case losses go up more than average losses. This, in turn, causes the cushion provided by Basel I requirements to drop relative to the benchmark case because Basel I is not sensitive to recovery rates. On the other hand, the ratios of the worst case capital to Basel II and Basel III requirements do not vary much because Basel II and III capital, being sensitive to recovery assumptions, adjust upward proportionally to the rise in worst case capital. Similarly, if recovery rates are moved by 10% over the benchmark case (Panel B) the ratios of worst case capital to Basel I requirements fall noticeably but the ratios for Basel II and III requirements are again only marginally affected.

So far, we have assumed that the recovery rates used by banks when calculating regulatory requirements are the same as those that actually materialise in the stress scenario. However, if a crisis is preceded by a prolonged boom period, as was the case before the 2008-2009 Great Recession, banks may internally use recovery rates that are calibrated on the more recent experience, which would be higher that those that occur in stress conditions. We have tested this scenario by assuming that banks base their regulatory capital calculations on the benchmark worst case recovery of 50% while in fact the actual worst case recovery turns out to be less favourable at 40%. The results are shown in Panel C. In this case all ratios indicate a noticeable deterioration of the regulatory cushion relative to unexpected worst case losses across all types of regulatory requirements, as one should expect.

5.2. Credit rating standards

Our analysis is based on the implicit assumption that Moody's rating standards have not changed significantly since the Great Depression. Only if this assumption holds it is acceptable to build a crisis scenario for a rating today by using that rating's default and migration rates during the Great Depression or any other stressed historical period since then. Moody's states that "the meaning of its ratings should be highly consistent over time" (Cantor and Mann, 2003), but in a relative sense. The rating agency aims to ensure that, at each point in time and over time, higher ratings are associated with lower default rates than lower ratings. However, it is not an objective of the agency to guarantee that the default rate of each rating does not vary over time. This is because ratings are through-the-cycle assessments. They measure the long-term credit quality of a company by giving low weight to temporary shocks that may alter the firm's credit standing in the short term but without lasting effect. This enables rating agencies to achieve a degree of stability in their ratings. Since ratings are used by a variety of market participants including investors, issuers, lenders and regulators for decisions on portfolio composition, financial covenants in debt contracts, capital allocations and capital requirements, a change in rating is only considered if it is unlikely it will be reversed in the near future. As a result, default rates associated with specific ratings may vary and do vary over time (see Figure 1) to reflect business or credit cycle fluctuations. Some authors, however, have argued that, even when accounting for cyclical fluctuations caused by a through-the-cycle rating system, ratings have not preserved their consistency over time. With a sample of S&P's ratings covering the period from 1978 to 1995 Blume et al (1998) employ a probit model to measure the probability of being assigned a specific rating conditional on firm-specific characteristics. They find that the annual intercept of the model, a proxy for the average credit rating, declines steadily over the sample, which they interpret as an indication of a secular tightening of credit rating standards. Amato and Furfine (2004) extend Blume et al's analysis by including in the probit model systematic risk factors derived by taking the cross-sectional average of the firm-specific risk factors.

They find that, in most cases, this eliminates the secular trend observed by Blume et al and, in the case of newly issued or recently updated ratings, the trend is reversed suggesting a relaxation of credit standards. Jorion et al (2005) also extend Blume et al's work by accounting for changes in the industrial composition of rated companies, increased manipulation of accounting data and other factors and obtain similar results to Amato and Furfine, thus refuting the presence of a secular trend. All the above studies, however, concern S&P's ratings. Zhou (2001) looks at ratings standards of Moody's between 1971 and 2000 and conclude that the standards, while accounting for business cycle effects, change through time but with a cyclical pattern with a period of relaxation in the 1970s and 1980s followed by a tightening from the mid-90s. Zhou suggests that a plausible explanation for the periods characterised by looser standards may be the increasing competition among rating agencies which forces them to give more generous ratings to retain existing customers or entice new ones. However, since standards cannot be relaxed indefinitely, also because of the reputational damage that may follow, rating agencies correct the trend and become stricter especially in the aftermath of a crisis. Bolton et al (2010) theoretically model this pattern and argue that ratings become inflated in boom periods and tighter during recessions. However, none of the above empirical contributions has investigated rating standards during and since the Great Depression.

To see if there is a secular trend in Moody's rating standards from the beginning of our sample, we have applied the simple approach of Zhou (2001) and fitted a linear trend on annual default rates for the various rating categories. Dummies that identify recessions have been included to capture increases in default rates due to changes in macro-economic conditions. The Aaa and Caa-C rating categories have been excluded from the analysis because the former has zero annual default rates across the whole sample and the default rates of the latter are affected by small sample problems, as discussed in the previous Section. A statistically significant and positive trend for a given rating category would indicate that default rates have increased over time for that rating, which would be attributed to a relaxation of its standard. On the contrary, a negative trend would indicate a tightening of its standard. Results are reported in Table 11. The coefficients of the linear trend are all negative across ratings with the exception of single-B. However, none of them is statistically significant. The results appear to suggest that there is no strong evidence of a marked change of rating standards over the sample. The default rates data in Figure 1, however, hints at the presence of a non-linear trend with a tightening of rating standards following the Great Depression, which may explain the low default rates through the 1950s and 1960s, and a subsequent relaxation that led to the higher default rates in the 1970s up until today. We have therefore fitted a quadratic trend to the series of default rates and found it to be statistically significant for all rating categories except single-B, when recession dummies are excluded. However, when we take into account the impact on default rates of macro-economic conditions by introducing recession dummies, the non linear trend loses significance for all ratings except Baa. So, Baa rating aside, the aggregate change in macro-economic conditions appears to explain the broad pattern observed in the data. The non-linear trend for the Baa rating resulting from our regression analysis (with recession dummies) is shown in Figure 10. It appears that the average credit quality of Baa rated firms increased up until the 1970s, which would correspond to a tightening of the Baa standard, followed by a decline in credit quality (i.e. relaxation of standard) in the remaining part of the sample. The Figure shows that, as a result of this reversal, Baa standards are heading back to the level in the Great Depression period but are not there yet. The overall trend implies that the default rates associated with the Baa rating during the Great Depression would probably be lower today if a Great Depression scenario was to represent itself. Then, the average credit quality of the portfolios employed in our analysis would be higher, while their credit losses associated with the Great Depression scenario would be lower, when measured in terms of today's credit ratings. This is particularly the case for the "High" and "Average" quality portfolios for which the Baa category represents a substantial proportion of assets (see Panel D in Table 7). To show the impact of today's higher standards of the Baa rating relative to the Great Depression period we have recomputed worst case capital to Basel capital ratios by assuming that Baa default and migration rates are the same as those of the higher single-A rating during the worst years of the Great Depression, i.e. between 1931 and 1935.[30] Results are shown in Table 12. As one should expect the ratios are

[30] It is plausible to assume single-A to be a lower bound for the default and downgrade risk of Baa as, historically, Baa annual default rates have almost never fallen below those of the single-A category. Over the past 90 years default rate "inversions" for the two categories were observed only three times in 1926, 1927 and 1936, all of which were relative benign years in terms of aggregate default rates. The size of the

significantly improved for the high and average quality portfolios (see Table 8 for a comparison). However, they change only marginally for the low and very low quality portfolios as their losses are dominated by defaults in the speculative grade ratings. Consistently with the results in Table 8, Basel 3 buffers are still inadequate to provide a sufficient cushion against Great Depression style losses for all portfolios and holding periods with the exception of high and average quality portfolios over a 1 year horizon.

6. Conclusion

In this paper, we estimate expected credit losses for individual exposures as well as representative bank portfolios under the Great Depression scenario. We derive worst case capital based on this scenario, test its sensitivity to holding period assumptions and to migration risk, and compare it with existing and proposed bank capital requirements. From our portfolio analysis we find that by expanding the holding period from one year, as currently assumed in Basel 2 and 3, to three years, worst case capital can increase more than three times. The inclusion of migration risk causes smaller but still sizeable rises. Our stress scenario analysis indicates that Basel 2 capital would be enough to absorb Great Depression style losses over the first year of the crisis. However, losses cumulating over the following years may exceed the capital requirement if the bank is unable to recapitalize. We find that over a three year horizon banks with low quality portfolios would not be able to limit losses within their Basel 2 required minimum. Under the so called Basel 3 agreement, which was put together by regulators in response to the recent crisis, bank capital requirements are large enough to absorb Great Depression-like losses. However, their decline would be substantial and, in many cases, far in excess of the capital buffers that have been introduced to ensure that banks survive crisis periods without government support.

Our results are based on a sample that is dominated by US companies. Then, one may question to what extent our Great Depression scenario and stress testing results may be

inversions is only 14 basis points on average. For comparison, during the worst years of the Depression, 1931-35, the Baa annual default rate exceeded the single-A default rate by 67 basis points on average.

applicable to other countries. It is not unreasonable to expect that qualitatively similar results may be found across several developed economies. Indeed, the Great Depression severely affected a number of nations, sometimes in remarkably similar ways. Bernanke and Mihov (2000) report that industrial production fell in Canada, US and Germany from June 1928 to its bottom level in 1932-33 by a comparable amount (49%, 45% and 41% respectively). The resilience of the crisis period was also an internationally common feature of the Great Depression. Reinhart and Rogoff (2009)[31] report that a 3 to 5 year contraction in output per capita was shared by 11 countries, namely, US, Canada, Indonesia, Italy, Austria, Germany, Poland, Argentina, Brazil, Chile and France. For 6 of these, including the US, it took between 10 and 12 years for output per capita to return to its pre-crisis levels.

Employing historical stress tests based on past crises is a popular method to establish the resilience of a bank to shocks. Clearly, the adoption of the Great Depression, the worst case scenario over the past century, as a benchmark stress test, could give markets and financial institutions greater confidence to operate in a stable manner in the event of future periods of instability and would shield governments and taxpayers more effectively against the costs of financial crises. Recent research that focuses on the costs and benefits of bank capital appears to indicate that more substantial capital levels, such as those implied by our analysis, may not only be feasible but also advisable.

[31] See Figures 14.7 and 14.8 on pages 234-36.

Appendix

In this Appendix we show that for a 1-year exposure, the worst case capital resulting from the model presented in Section 2 and the IRB capital in Basel 2 are consistent with one another. The IRB capital requirement K_{IRB} for a wholesale corporate exposure is defined as,

$$K_{IRB} = CF \cdot MA \cdot \left[(1-a_{IRB})P_{D,1} - (1-a_{IRB})P_{A,1}\right] \cdot EAD \qquad \text{(A.1)}$$

where CF is a calibration factor introduced to "broadly maintain the aggregate level of [minimum capital] requirements" to the pre-Basel II level;[32] MA is a "maturity adjustment" employed to rescale the capital charge to make it an increasing function of the exposure's duration;[33] $P_{D,1}$, the probability of default under a stress scenario (termed "downturn PD"), is computed as a function of the average default probability $P_{A,1}$ with a pre-specified formula (see Basel Committee 2006, p. 64); EAD is the exposure at default and a_{IRB} the recovery rate. For more details about (A.1) see, for example, Resti and Sironi (2007).[34] Then, for a one-year exposure and an EAD normalised to 1, the corresponding measure for the difference $L_W - L_A$ in our model (see equation 5) is given in the IRB through the difference of the terms inside the square brackets in (A.1), i.e. $(1-a_{IRB})P_{D,1}$, which represents the expected loss in a downturn, and $(1-a_{IRB})P_{A,1}$, the average expected loss. To see the consistency, for a 1-year exposure, between the worst case capital resulting from our model and the IRB capital we need to "harmonise" their underlying assumptions, which differ in several respects: (1) our 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

[32] Basel Committee (2006), page 4, paragraph 14.
[33] 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)
[34] See pp. 603-612.

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. If we harmonise the assumptions as follows: (i) set interest rates to zero and (ii) the recovery rate in our model to be constant, i.e. $a_W = a_A = a$, (iii) express the IRB recovery as a percentage of par, that is $a_{IRB} = a/(1+C)$, and (iv) ignore the calibration factor *CF,* then, worst case capital and IRB capital for a one-year exposure become remarkably similar,

$$\text{Model: } \frac{K_W}{G} = \frac{(P_{W,1} - P_{A,1})(1 + C - a)}{1 + C} \tag{A.2}$$

$$\text{IRB: } \frac{K_{IRB}}{EAD} = \frac{(P_{D,1} - P_{A,1})(1 + C - a)}{1 + C} \tag{A.3}$$

where $P_{W,1}$ and $P_{A,1}$ are the worst case and average 1-year default rates over the sample period, respectively. For a 1-year exposure and zero interest rates $G = EAD = (1 + C)$ so the above capital definitions will be expressed as ratios with respect to the same denominator and thus will be directly comparable. For exposures with maturity longer than 1 year the two measures of capital can be compared by rescaling the model's worst case capital by G/EAD.

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Table 1. Worst Time Periods based on Cumulative Default Rates

The table shows time periods of various length with the highest cumulative default rate. Cumulative default rates have been computed from the 1921-2009 time series of annual default rates across all rating categories.

Length in years	Start	End	Cumulative Default Rate
1	1933	1933	8.90
2	1932	1933	14.10
3	1931	1933	17.55
4	1932	1935	20.89
5	1931	1935	24.07
6	1931	1936	25.43
7	1931	1937	26.76
8	1931	1938	28.37
9	1931	1939	29.48
10	1931	1940	30.86

Table 2: Average, Great Depression, Great Recession and Worst Case Transition Matrices

All figures are in percent. The transition mobility reported at the bottom of each matrix is measured with the singular value indicator of Jafry and Schuermann (2004).

Panel A: 1921-2009 Average transition matrix

	Aaa	Aa	A	Baa	Ba	B	Caa-C	D
Aaa	92.29	6.57	0.92	0.20	0.02	0.00	0.00	0.00
Aa	1.22	91.70	6.24	0.61	0.14	0.01	0.01	0.07
A	0.08	2.53	91.42	5.12	0.63	0.10	0.02	0.10
Baa	0.04	0.25	4.12	89.52	4.99	0.71	0.08	0.28
Ba	0.01	0.08	0.43	5.31	86.45	6.05	0.53	1.14
B	0.00	0.04	0.13	0.66	5.91	85.61	4.01	3.64
Caa-C	0.00	0.02	0.04	0.39	1.25	5.52	78.11	14.67

JS Mobility: 11.68

Panel B: Great Recession transition matrix (2008-2009 average)

	Aaa	Aa	A	Baa	Ba	B	Caa-C	D
Aaa	76.20	23.50	0.00	0.30	0.00	0.00	0.00	0.00
Aa	0.00	81.06	17.53	0.76	0.22	0.00	0.14	0.28
A	0.00	0.81	89.07	9.22	0.28	0.28	0.05	0.28
Baa	0.00	0.15	1.68	91.73	5.06	0.60	0.15	0.65
Ba	0.00	0.00	0.10	4.51	78.95	12.54	2.04	1.86
B	0.00	0.00	0.09	0.14	2.92	76.33	15.64	4.87
Caa-C	0.00	0.00	0.00	0.00	0.00	5.24	68.98	25.78

JS Mobility: 20.95

Panel C: Great Depression transition matrix (1931-1935 average)

	Aaa	Aa	A	Baa	Ba	B	Caa-C	D
Aaa	82.70	12.15	4.57	0.58	0.00	0.00	0.00	0.00
Aa	2.13	80.16	13.01	3.12	1.15	0.13	0.00	0.29
A	0.12	3.30	77.29	14.51	3.65	0.47	0.00	0.67
Baa	0.09	0.16	3.19	75.28	17.16	2.69	0.09	1.34
Ba	0.00	0.00	0.04	5.35	69.60	17.70	1.44	5.87
B	0.00	0.00	0.06	0.40	7.09	68.15	14.03	10.27
Caa-C	0.00	0.00	0.00	0.26	0.65	7.00	67.94	24.15

JS Mobility: 25.51

Panel D: Worst Case Transition Matrix (1932)

	Aaa	Aa	A	Baa	Ba	B	Caa-C	D
Aaa	67.65	20.59	10.29	1.47	0.00	0.00	0.00	0.00
Aa	1.74	53.47	32.99	7.29	3.47	0.35	0.00	0.69
A	0.31	1.23	56.00	31.69	8.62	1.23	0.00	0.92
Baa	0.00	0.00	0.94	53.30	36.32	8.49	0.00	0.94
Ba	0.00	0.00	0.00	0.22	50.22	38.86	4.37	6.33
B	0.00	0.00	0.00	0.00	1.29	54.38	29.12	15.21
Caa-C	0.00	0.00	0.00	1.32	1.32	2.63	68.42	26.32

JS Mobility: 44.47

Table 3. Minimum and Average Recovery Rates for Bank Loans in the Literature

Minimum and average recovery are computed from time series of mean annual recovery rates

Paper	Minimum Recovery (%)	Average Recovery (%)	Notes
Araten et al (2004)	46.50	63.06	JPMorgan Chase data, 1982-1999 sample. Minimum and average recoveries estimated from statistics reported in Table 6.
Asarnow et al (1995)	52.39	66.04	Citigroup data, 1970-1993 sample. Minimum and average recoveries estimated from statistics reported in Table 1 for years with more than 10 default observations (i.e. from 1974 to 1993).
Emery (2008)	50.00	65.00	Projections based on Moody's data and on recovery assumptions for issuers with only bank loans outstanding and no bonds outstanding. See footnote 16.
Felsovalyi et al (1998)	53.40	69.66	Citibank data, 1970-1996 sample. Minimum and average recoveries based on statistics reported in Table 4.

Table 4: Worst Case Default Loss, Average Default Loss and Worst Case Capital based on the Great Depression Scenario

Worst case loss, average loss and worst case capital are defined as in equation (3), (4) and (5) in the text. The worst case loss in the shaded area is unrelated to the Great Depression. Losses are derived with and without migration risk. Minimum and average recovery rate assumptions are 50% and 65% respectively. All figures are in percent. Calculations are based on the 1921-2009 sample of Moody's annual transition matrices.

	Aaa	Aa	A	Baa	Ba	B
Holding			Panel A: Default Risk only			
Period (yrs)			Worst Case Loss			
1	0.00	0.45	0.90	1.06	5.92	10.14
2	0.00	0.45	1.19	1.71	8.71	14.91
3	0.00	0.88	1.46	2.40	9.98	18.46
			Average Loss			
1	0.00	0.02	0.03	0.10	0.40	1.31
2	0.00	0.05	0.07	0.19	0.79	2.53
3	0.00	0.07	0.10	0.28	1.18	3.72
			Worst Case Capital			
1	0.00	0.42	0.87	0.96	5.51	8.83
2	0.00	0.40	1.13	1.52	7.92	12.37
3	0.00	0.81	1.36	2.11	8.81	14.74
			Panel B: Default Risk and Migration Risk			
			Worst Case Loss			
1	0.00	0.45	0.90	1.06	5.92	10.14
2	0.07	0.69	1.42	3.77	10.02	16.55
3	0.19	1.11	2.01	5.47	12.39	20.44
			Average Loss			
1	0.00	0.02	0.03	0.10	0.40	1.31
2	0.00	0.05	0.08	0.24	0.88	2.66
3	0.01	0.08	0.15	0.42	1.41	3.97
			Worst Case Capital			
1	0.00	0.42	0.87	0.96	5.51	8.83
2	0.06	0.64	1.33	3.53	9.14	13.89
3	0.18	1.03	1.86	5.05	10.98	16.47
			Panel C: Effect of Migration Risk (Panel B minus Panel A)			
			Worst Case Loss			
1	0.00	0.00	0.00	0.00	0.00	0.00
2	0.07	0.24	0.22	2.06	1.31	1.64
3	0.19	0.23	0.55	3.07	2.41	1.98
			Average Loss			
1	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.02	0.05	0.09	0.12
3	0.01	0.01	0.05	0.14	0.24	0.25
			Worst Case Capital			
1	0.00	0.00	0.00	0.00	0.00	0.00
2	0.06	0.24	0.20	2.00	1.22	1.52
3	0.18	0.22	0.50	2.93	2.17	1.73

Table 5. Sensitivity of Worst Case Capital To Interest Rate Assumptions

The table shows the change in worst case capital (WCC) when interest rates increase from 0% to 3% and 6%. Worst case capital is computed by taking into account default risk and migration risk. Figures are in percent.

Holding Period (yrs)	Aaa	Aa	A	Baa	Ba	B
	Panel A: WCC with 3% interest minus WCC with 0% interest					
1	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	-0.01	-0.01	-0.01	-0.07	-0.15
3	0.00	-0.03	-0.05	-0.05	-0.14	-0.31
	Percentage Change					
1	na	0.00	0.00	0.00	0.00	0.00
2	0.00	-1.43	-0.90	-0.25	-0.80	-1.11
3	-0.33	-2.65	-2.70	-0.91	-1.30	-1.85
	Panel B: WCC with 6% interest minus WCC with 0% interest					
1	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	-0.02	-0.02	-0.02	-0.15	-0.31
3	0.00	-0.06	-0.10	-0.09	-0.29	-0.61
	Percentage Change					
1	na	0.00	0.00	0.00	0.00	0.00
2	0.00	-2.85	-1.80	-0.50	-1.60	-2.22
3	-0.67	-5.35	-5.44	-1.84	-2.61	-3.73

Table 6: Ratios of Worst Case Capital to Basel 1, Basel 2 and Basel 3 Capital across Ratings

This Table shows the ratios of worst case capital to Basel 1, Basel 2, Basel 3 capital and Basel 3 capital buffers across ratings and maturities. Basel 2 is computed with the internal rating based approach (IRB). Basel 3 is given by the Basel 2 capital plus a buffer totalling 5% of risk weighted assets. Shaded areas indicate instances when worst case capital exceeds regulatory capital (Panel A, B and D) or the capital buffer (Panel C). Minimum and average recovery rate assumptions are 50% and 65% respectively. *The maturity of an asset with a given rating coincides with the investment horizon (or holding period) for that asset when estimating worst case capital. On the other hand, Basel capital requirements assume a 1 year holding period, regardless of the maturity of the asset.

Rating	Aaa	Aa	A	Baa	Ba	B
Maturity* (yrs)			Panel A: Basel 1			
1	0.0	5.3	10.9	12.0	68.9	110.4
2	0.8	7.9	16.6	44.1	114.8	176.1
3	2.3	12.9	23.3	63.3	138.5	211.6
			Panel B: Basel 2			
1	0.0	31.6	50.7	27.4	75.3	78.8
2	5.4	32.8	55.5	79.0	107.6	113.9
3	11.5	40.6	60.4	93.2	113.9	125.4
			Panel C: Basel 3 Buffers			
1	0.0	50.6	81.1	43.9	120.4	126.1
2	8.7	52.5	88.9	126.5	172.2	182.3
3	18.3	65.0	96.7	149.2	182.2	200.7
			Panel D: Basel 3			
1	0.0	19.5	31.2	16.9	46.3	48.5
2	3.3	20.2	34.2	48.6	66.2	70.1
3	7.1	25.0	37.2	57.4	70.1	77.2

Table 7: Portfolio Losses and Worst Case Capital based on the Great Depression Scenario

Worst case loss, average loss and worst case capital are defined as in equation (3), (4) and (5) in the text. Losses are derived with and without migration risk. Portfolios compositions for high, average, low and very low credit quality are as reported in Gordy 2000, p. 132, Table 1. Highlighted areas in Panel D indicate median ratings. All figures are in percent and based on the 1921-1960 time series of Moody's annual transition matrices. Minimum and average recovery rate assumptions are 50% and 65% respectively.

	Portfolio Credit Quality			
	High	Average	Low	Very Low
		Panel A: Default Risk Only		
Holding Period (yrs)		Worst Case Loss		
1	1.91	3.73	6.15	6.77
2	3.08	5.98	10.07	11.18
3	3.80	7.39	12.51	14.01
		Average Loss		
1	0.23	0.42	0.68	0.78
2	0.45	0.82	1.32	1.52
3	0.66	1.21	1.95	2.25
		Worst Case Capital		
1	1.69	3.32	5.48	5.99
2	2.63	5.16	8.75	9.65
3	3.14	6.18	10.56	11.76
		Panel B: Default and Migration Risk		
		Worst Case Loss		
1	1.91	3.73	6.15	6.77
2	4.57	7.46	11.52	12.57
3	6.06	9.69	14.69	16.07
		Average Loss		
1	0.23	0.42	0.68	0.78
2	0.49	0.87	1.38	1.58
3	0.79	1.34	2.10	2.38
		Worst Case Capital		
1	1.69	3.32	5.48	5.99
2	4.07	6.60	10.14	10.99
3	5.27	8.34	12.58	13.69

Table 7 – continued

	Portfolio Credit Quality			
	High	Average	Low	Very Low
	Panel C: Effect of Migration Risk (Panel B minus Panel A)			
Holding Period (yrs)	Worst Case Loss			
1	0.00	0.00	0.00	0.00
2	1.48	1.49	1.44	1.39
3	2.26	2.30	2.18	2.06
	Average Loss			
1	0.00	0.00	0.00	0.00
2	0.05	0.05	0.06	0.06
3	0.13	0.13	0.15	0.13
	Worst Case Capital			
1	0.00	0.00	0.00	0.00
2	1.44	1.44	1.38	1.33
3	2.13	2.17	2.03	1.93
Rating	Panel D: 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
Baa	37.92	31.16	16.54	13.2
Ba	19.08	32.44	38.06	35.6
B	2.72	11.12	32.36	37.02
Caa	1.3	3.98	6.8	9.5

Table 8: Ratios of Worst Case Capital to Basel 1, Basel 2 and Basel 3 Capital across Portfolios

This table shows the ratios of worst case capital to Basel 1, Basel 2 Basel 3 regulatory capital and to Basel 3 capital buffers for stylised bank portfolios of different credit quality. Basel 2 is computed with the internal rating based approach (IRB). Basel 3 is given by the Basel 2 capital plus a buffer equal to 5% of risk weighted assets. Shaded areas indicate instances when worst case capital exceeds regulatory capital (Panel A, B and D) or the capital buffer (Panel C). Calculations are based on the 1921-1960 time series of Moody's annual transition matrices. Minimum and average recovery rate assumptions are 50% and 65% respectively. *The maturity of a portfolio coincides with the investment horizon (or holding period) for that portfolio when estimating worst case capital. On the other hand, Basel capital requirements assume a 1 year holding period, regardless of the maturity of the portfolio.

	Portfolio Credit Quality			
	High	Average	Low	Very Low
Maturity* (yrs)	Panel A: Basel 1			
1	21.1	41.5	68.4	74.9
2	51.3	83.4	128.6	139.7
3	66.8	106.9	162.2	177.3
	Panel B: Basel 2			
1	43.2	56.8	64.7	65.0
2	85.5	97.7	107.6	108.3
3	94.1	109.4	121.9	124.2
	Panel C: Basel 3 buffers			
1	69.1	90.9	103.5	104.1
2	136.8	156.4	172.2	173.2
3	150.6	175.0	195.0	198.7
	Panel D: Basel 3			
1	26.6	35.0	39.8	40.0
2	52.6	60.1	66.2	66.6
3	57.9	67.3	75.0	76.4

Table 9. Great Depression Implied Capital Buffers

This table shows capital buffers, as a percentage of Basel 3-risk weighted assets, that a bank should hold to match Great Depression unexpected losses (i.e. worst case capital based on the Great Depression scenario). Implied buffers are reported for individual rating categories and stylised bank portfolios of different credit quality. Shaded areas indicate implied buffers that exceed the current Basel 3 buffer requirement of 5%.

	Credit Rating					
Holding Period (yrs)	Aaa	Aa	A	Baa	Ba	B
1	0.0	2.5	4.1	2.2	6.0	6.3
2	0.4	2.6	4.4	6.3	8.6	9.1
3	0.9	3.3	4.8	7.5	9.1	10.0

	Portfolio Credit Quality			
	High	Average	Low	Very Low
1	3.5	4.5	5.2	5.2
2	6.8	7.8	8.6	8.7
3	7.5	8.7	9.7	9.9

Table 10. Recovery Rate Sensitivity of Worst Case Capital to Basel Capital Ratios

This table shows the ratios of worst case capital to Basel 1, Basel 2 Basel 3 regulatory capital and to Basel 3 capital buffers for stylised bank portfolios of different credit quality under various recovery rate assumptions. Basel 2 is computed with the internal rating based approach (IRB). Basel 3 is given by the Basel 2 capital plus a buffer equal to 5% of risk weighted assets. Shaded areas indicate instances when worst case capital exceeds Basel 1, 2 or 3 regulatory capital or the Basel 3 capital buffer. Calculations are based on the 1921-1960 time series of Moody's annual transition matrices. *The maturity of a portfolio coincides with the investment horizon (or holding period) for that portfolio when estimating worst case capital. On the other hand, Basel capital requirements assume a 1 year holding period, regardless of the maturity of the portfolio.

	Portfolio Credit Quality			
	High	Average	Low	V. Low
		Panel A. Recovery Rate Assumptions: Minimum 40%, Average 55%		
Maturity* (yrs)		**Basel 1**		
1	25.0	49.1	81.1	88.6
2	60.8	98.7	151.9	164.8
3	79.0	126.0	190.8	208.1
		Basel 2		
1	42.7	56.3	64.2	64.5
2	84.7	96.7	106.5	107.1
3	92.9	107.8	120.0	122.2
		Basel 3 buffers		
1	68.4	90.2	102.7	103.2
2	135.6	154.8	170.4	171.3
3	148.7	172.5	192.0	195.5
		Basel 3		
1	26.3	34.7	39.5	39.7
2	52.1	59.5	65.5	65.9
3	57.2	66.3	73.9	75.2
		Panel B. Recovery Rate Assumptions: Minimum 60%, Average 75%		
Maturity* (yrs)		**Basel 1**		
1	17.2	33.8	55.8	61.2
2	41.7	68.1	105.3	114.6
3	54.6	87.8	133.7	146.4
		Basel 2		
1	43.8	57.6	65.5	65.8
2	86.7	99.2	109.3	110.0
3	95.9	111.7	124.6	127.2
		Basel 3 buffers		
1	70.1	92.1	104.7	105.3
2	138.8	158.7	174.9	176.0
3	153.4	178.7	199.4	203.5
		Basel 3		
1	27.0	35.4	40.3	40.5
2	53.4	61.0	67.3	67.7
3	59.0	68.7	76.7	78.3

Table 10 – continued

Panel C. Recovery Rate Assumptions:
Minimum 40%, Average 55% for Worst Case Capital
Minimum 50% for Basel Capital

Maturity* (yrs)				
		Basel 1		
1	25.0	49.1	81.1	88.6
2	60.8	98.7	151.9	164.8
3	79.0	126.0	190.8	208.1
		Basel 2		
1	51.2	67.3	76.6	77.0
2	101.5	115.6	127.1	127.7
3	111.3	128.9	143.3	145.8
		Basel 3 buffers		
1	81.9	107.8	122.6	123.1
2	162.4	185.0	203.4	204.4
3	178.1	206.3	229.3	233.3
		Basel 3		
1	31.5	41.4	47.2	47.4
2	62.4	71.2	78.2	78.6
3	68.5	79.3	88.2	89.7

Table 11. Time trend in 1-year default rates

This table shows the results of regressions of annual default rates on a linear (Panel A) and non-linear (Panel B) time trend for different rating categories. Sample period 1921-2009. t-statistics are computed with Newey-West standard deviations to account for autocorrelation and heteroscedasticity.

Panel A. Regression of annual default rates on a linear trend

	Trend		Adjusted
	Coefficient	t-statistic	R-squared
Rating	With NBER recession dummies		
Aa	-0.002	-0.95	0.267
A	-0.003	-1.07	0.476
Baa	-0.006	-1.34	0.187
Ba	-0.002	-0.22	0.650
B	0.044	1.63	0.575
	Without NBER recession dummies		
Aa	-0.002**	-2.18	0.061
A	-0.003*	-1.87	0.079
Baa	-0.006***	-2.92	0.097
Ba	-0.008	-0.68	0.003
B	0.034	1.27	0.031

Panel B. Regression of annual default rates on a non-linear trend

	Trend		Trend^2		Adjusted
	Coefficient	t-statistic	Coefficient X1000	t-statistic	R-squared
Rating	With NBER recession dummies				
Aa	-0.008	-1.15	0.062	1.17	0.280
A	-0.013	-1.34	0.108	1.38	0.509
Baa	-0.038***	-2.68	0.336**	2.62	0.312
Ba	-0.037	-0.87	0.358	0.94	0.656
B	0.035	0.30	0.096	0.08	0.567
	Without NBER recession dummies				
Aa	-0.011***	-4.10	0.095***	3.88	0.130
A	-0.013**	-2.42	0.110**	2.40	0.125
Baa	-0.032**	-3.41	0.286***	3.41	0.212
Ba	-0.063*	-1.72	0.615*	1.89	0.037
B	-0.046	-0.52	0.882	0.93	0.035

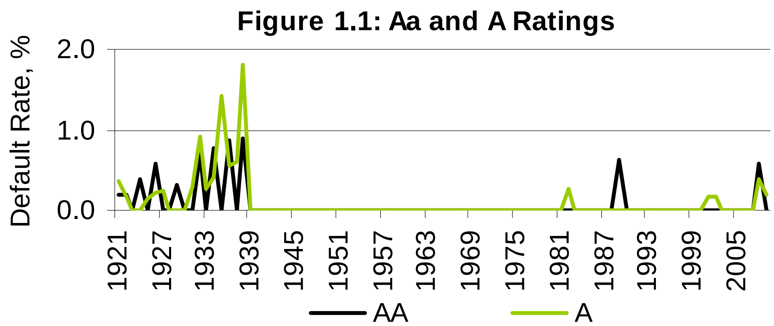
Table 12. Worst Case Capital to Basel Capital Ratios Under the Assumption of Tighter Baa Credit Standards During the Great Depression

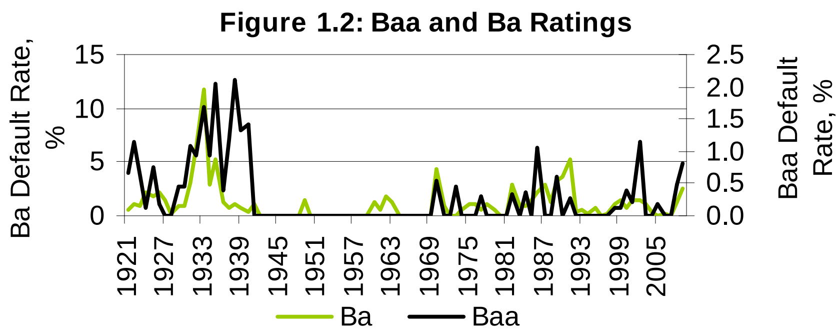
This table shows the ratios of worst case capital to Basel 1, Basel 2 Basel 3 regulatory capital and to Basel 3 capital buffers for stylised bank portfolios of different credit quality under the assumption that Baa default and migration rates over the 1931-1935 period are the same as for the single-A rating category. Basel 2 is computed with the internal rating based approach (IRB). Basel 3 is given by the Basel 2 capital plus a buffer equal to 5% of risk weighted assets. Shaded areas indicate instances when worst case capital exceeds Basel 1, 2 or 3 regulatory capital or the Basel 3 capital buffer. Calculations are based on the 1921-1960 time series of Moody's annual transition matrices. *The maturity of a portfolio coincides with the investment horizon (or holding period) for that portfolio when estimating worst case capital. On the other hand, Basel capital requirements assume a 1 year holding period, regardless of the maturity of the portfolio.

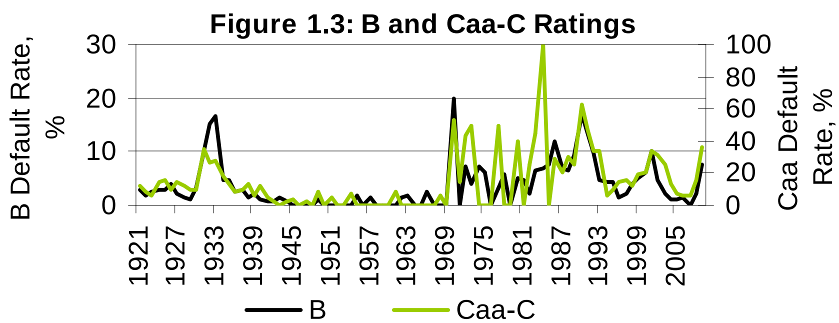
	Portfolio Credit Quality			
	High	Average	Low	Very Low
Maturity* (yrs)		Panel A: Basel 1		
1	17.9	38.9	67.1	73.8
2	38.7	73.4	123.4	135.5
3	47.6	90.9	153.8	170.5
		Panel B: Basel 2		
1	36.6	53.2	63.4	64.1
2	64.6	86.0	103.2	105.0
3	67.0	93.0	115.5	119.4
		Panel C: Basel 3 buffers		
1	58.6	85.2	101.4	102.5
2	103.3	137.5	165.2	168.0
3	107.2	148.9	184.8	191.1
		Panel D: Basel 3		
1	22.6	32.8	39.0	39.4
2	39.7	52.9	63.5	64.6
3	41.2	57.3	71.1	73.5

Figure 1

Moody's Annual Default Rates







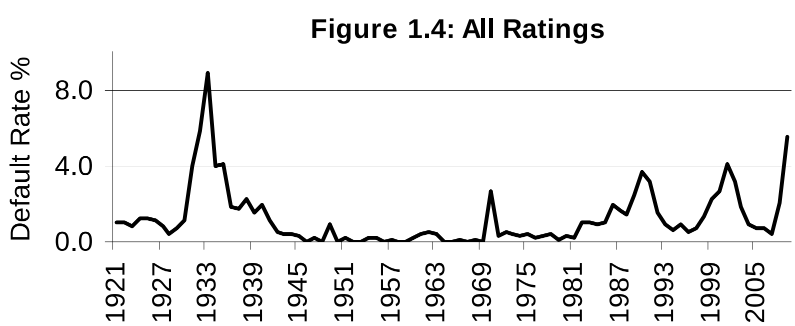


Figure 2

Transition Mobility and Default Rate

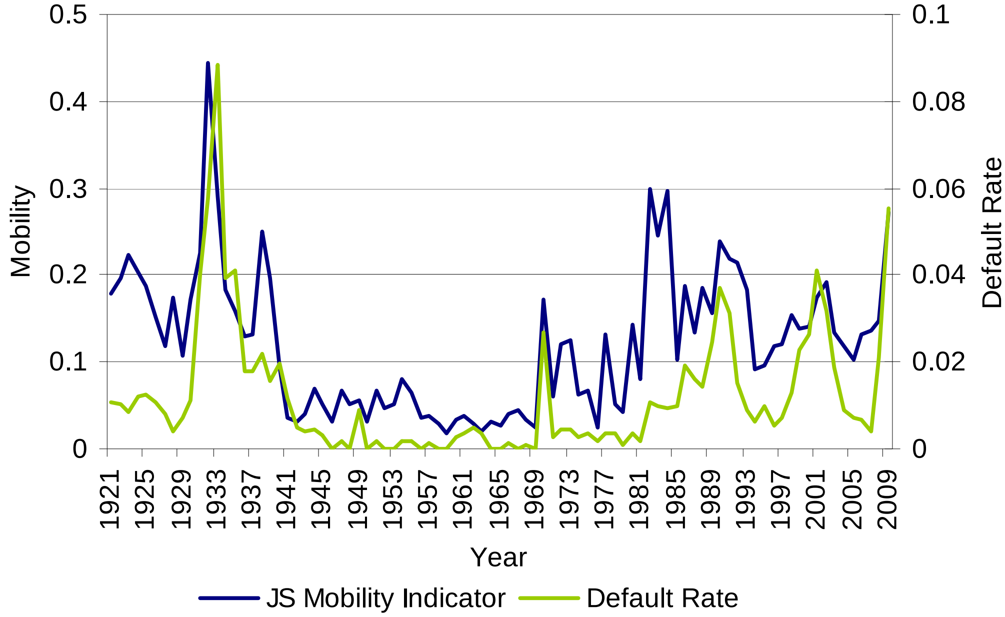


Figure 3

Transition Mobility and Recessions

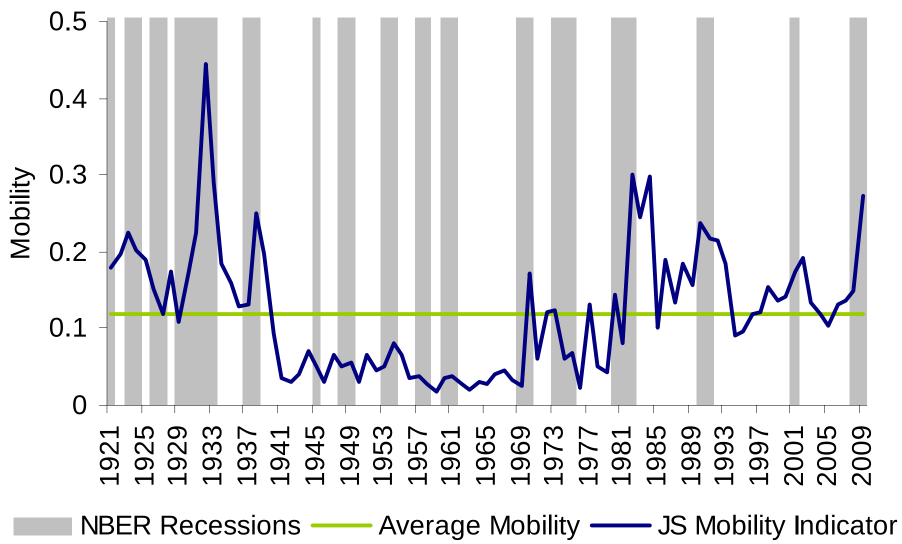


Figure 4

Bond Recoveries in the Great Depression Period

All the recovery data in the figure have been estimated from bond prices at or within a month from default as percentages of par value. Great Depression data is based on value weighted average recoveries of combined large and small bond issues reported in Hickman (1960), Table 150. Downturn data for 1990-92 and 2000-02 is taken from the "all bonds" column in Moody's (2010), Exhibit 21.

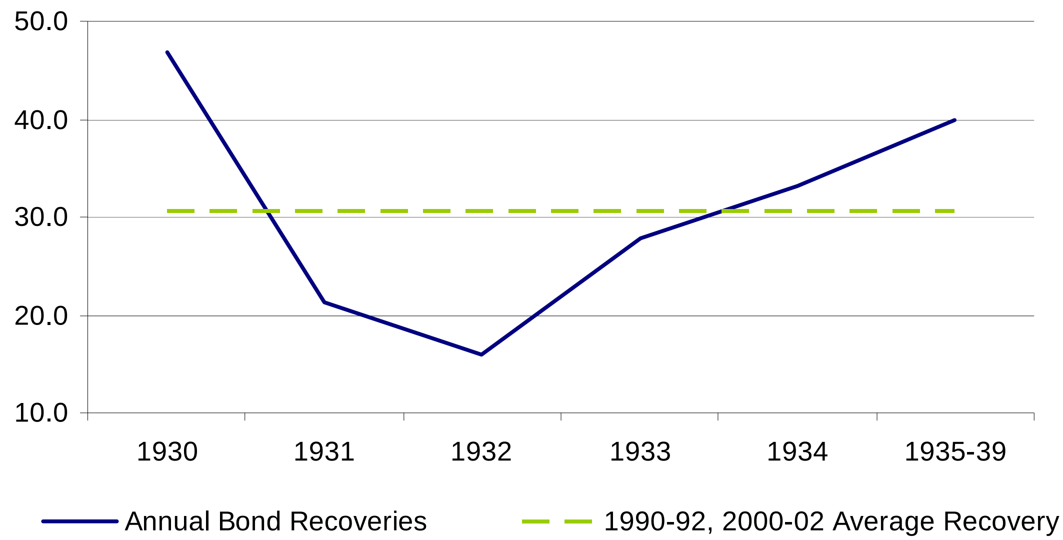


Figure 5

Number of Issuers and Default Rates for Caa-C Rated Firms

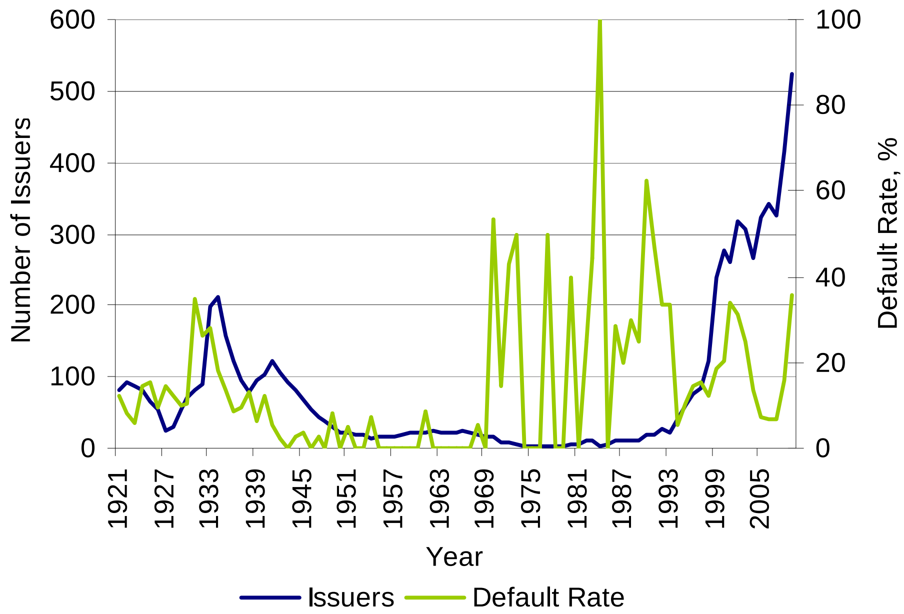


Figure 6: **Great Depression Buffers and Basel 3 Buffers across Ratings**
The figure shows the behaviour of Great Depression (GD) buffers based on our estimates of worst case capital, Basel 3 buffers and the cumulative probability of default. All three measures are based on a three year holding horizon. Sample period: 1921-2009.

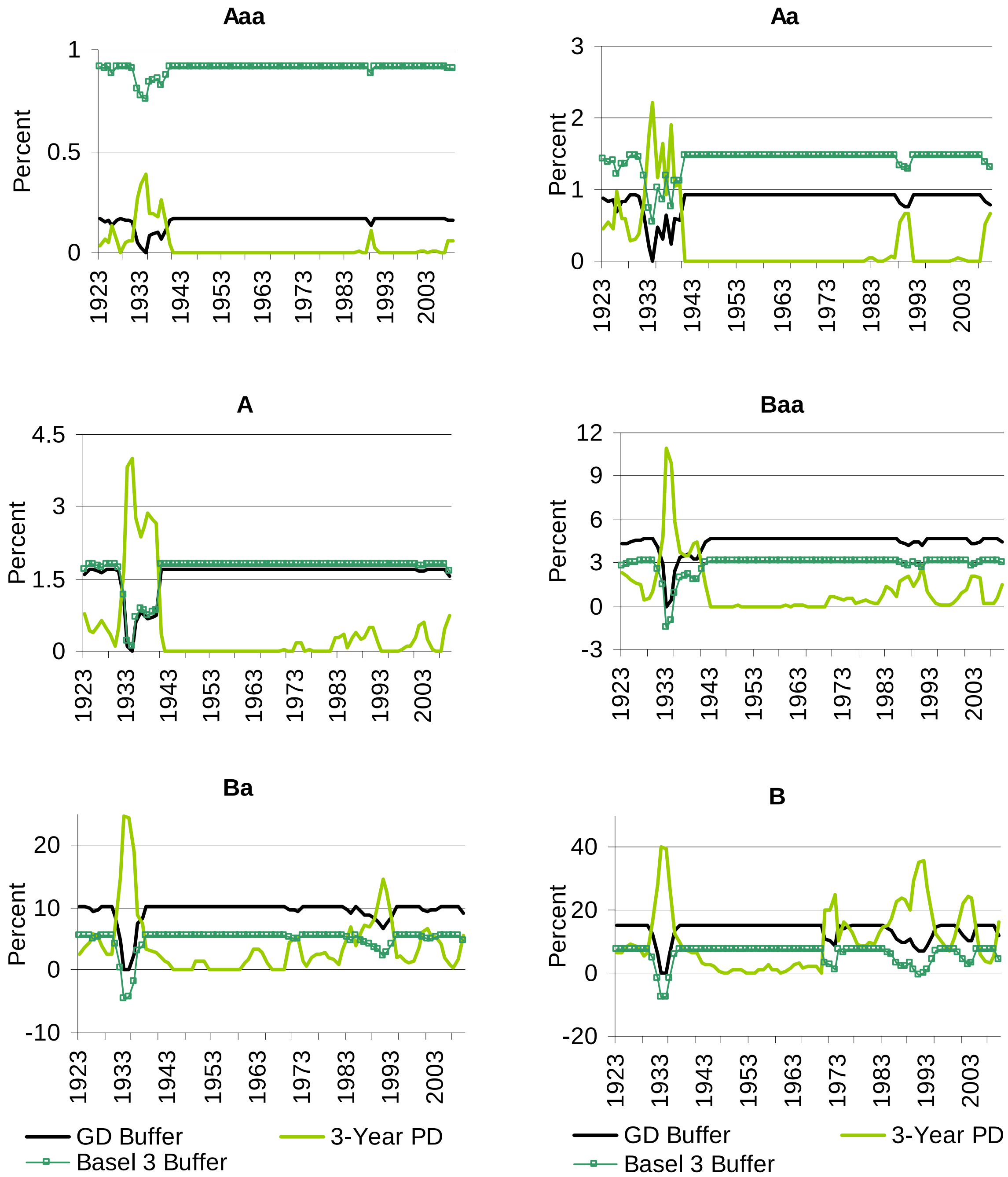


Figure 7: **Great Depression Buffers and Basel 3 Buffers across Portfolios**
The figure shows the behaviour of Great Depression (GD) buffers based on our estimates of worst case capital, Basel 3 buffers and the cumulative probability of default for high, average, low and very low quality portfolios. All three measures are based on a three year holding horizon. Sample period: 1921-1960.

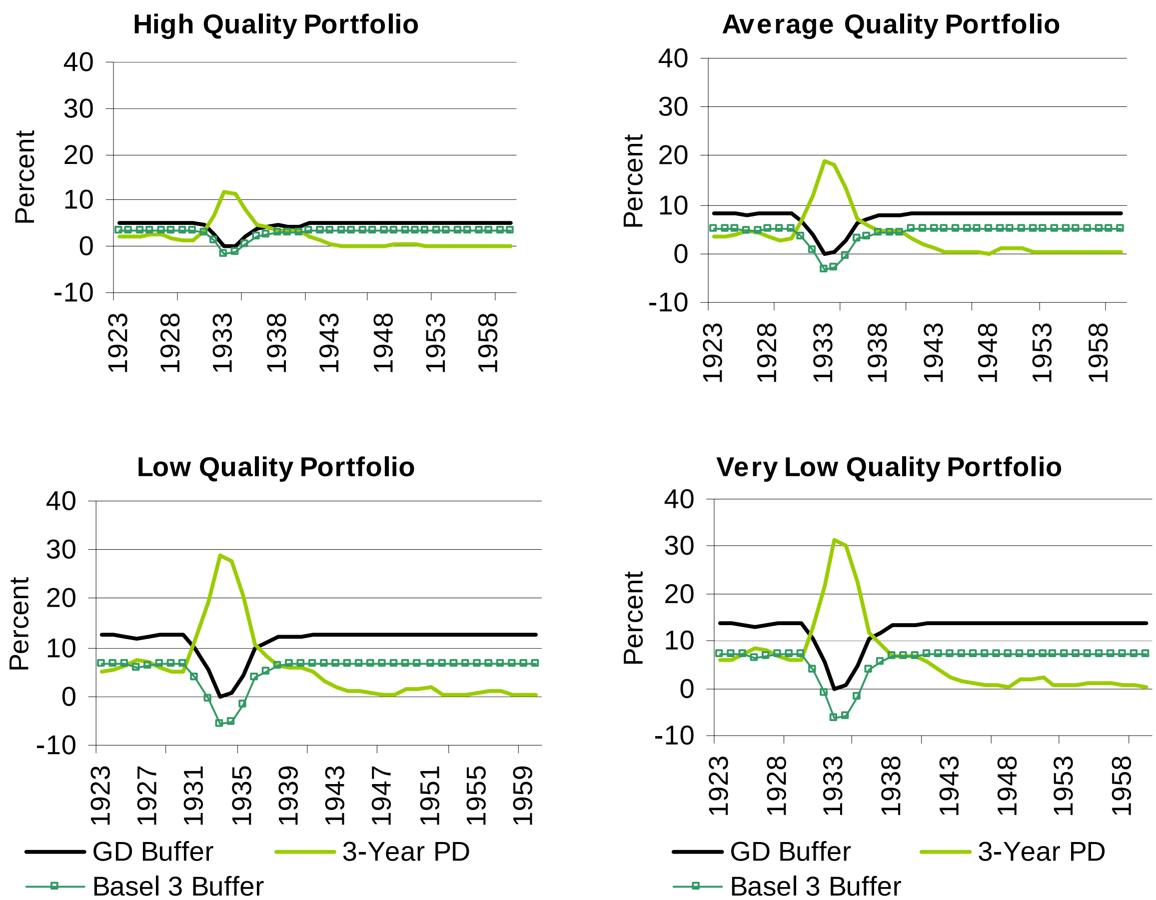


Figure 8
Non-Linear Trend in Baa Default Rates