Financial Crises and Credit Risk Capital for Buy and Hold Investors

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Abstract

Measuring portfolio losses on the basis of market prices may not be meaningful for buy and hold investors, even less so in periods of market turmoil. In this paper, we propose a new methodology to assess the potential loss, and the corresponding capital allocation, faced by buy and hold investors in their credit portfolios. Our method does not rely on current market prices and employs, as a primary input, historical default frequencies that allow us to account for downturn scenarios as severe as the Great Depression. Our derivation of credit risk capital does not rely on simulations nor distributional assumptions which makes it quick and easy to implement. As we focus on exposures held to maturity, our approach should prove particularly useful to commercial banks, life insurers and pension funds. We conclude the paper with a comparison of our risk measures with those derived under Basel II, the new and controversial regulatory framework for bank capital.

Keywords: Credit Risk, Financial Crisis, Economic Capital, Basel II.

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

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1. Introduction

The global financial crisis started in 2007 has starkly highlighted the difficulty, in periods of high instability, of extracting useful information from market prices for valuation, portfolio selection and capital allocation purposes. The Securities and Exchange Commission and the Financial Accounting Standards Board in a joint statement on September 30th 2008 have indicated that market prices should not be considered "determinative" when measuring fair value in illiquid or distressed markets. Many believe that mark-to-market accounting may have exacerbated the recent credit crisis creating a vicious circle in which fire-sale prices lead to over-conservative credit exposure valuations, which in turn fuel additional fire sales.[1] In this climate, where prices clearly do not reflect fundamentals but fundamental uncertainty or panic, the quantification of asset and portfolio risk based on market prices may lead to both inaccurate and unstable risk measures. This in turn may result in sub-optimal portfolio and capital allocations. In this paper, we explore a new approach to credit risk measurement that allows us to obtain meaningful and stable risk measures even in periods of substantial market turmoil. Our focus is on buy-and-hold investors. As this type of investors suffers credit losses only in the event of default, i.e. they are not affected by temporary market fluctuations, we do not make use of market price information and estimate potential credit losses primarily on the basis of historical default information.

Our credit risk measures are estimated with the risk neutral valuation approach introduced by Elton, Gruber, Agrawal and Mann (2001) (EGAM). The EGAM valuation method is based on a standard binomial model in which only two states are considered, default and non-default. This is acceptable provided the investor holds his assets to maturity, which is a plausible assumption in the case of the unsecuritised loan portfolios

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[1] This view was expressed by Ben Bernanke, the Federal Reserve chairman, in a Senate testimony on September 23rd, 2008. Mr Bernanke stated that: "Accounting rules require banks to value many assets at something close to a very low fire sale price rather than the hold-to-maturity price. However, this leads to big write-downs and reductions in capital, which in turn forces additional asset sales that send the fire sale price down further, adding to pressure."

of commercial banks and, for the most part, the corporate bond holdings of life insurance companies and pension funds, which are typically characterised by low rebalancing activity. The advantages of the EGAM model is that (1) it is not a structural model of default and therefore is not based on any specific distributional assumption and (2) it can be implemented with minimal data input, namely the term structure of default rates and the expected recovery rate in case of default.

The data we employ are Moody's historical default rates observed in the corporate bond market. The benefit of such database is that default histories cover a long period of time which is essential in order to produce credible distress scenarios and, as a result, meaningful credit loss estimates. Moody's default data stretch back for almost 90 years and include the Great Depression, which was characterised by the most severe default experience ever recorded. These types of stress scenarios have the advantage that the credit loss they produce has a clear and intuitive interpretation and do not depend on subjective assumptions.[2] By contrast, traditional value-at-risk measures often quantify credit risk and capital on the basis of ad hoc distributional assumptions, and of confidence levels that imply observation periods that are far longer than any currently available historical information, which makes model validation challenging, at best.

One obvious question is whether the data we employ may be used to assess the risk of credit exposures other than corporate bonds. Of particular practical value would be their applicability to corporate bank loans. However, default histories for bank exposures typically span only short periods of time. Indeed, banks, spurred by Basel II requirements, have only recently started to design sophisticated and far reaching internal rating systems and to collect in a systematic way default data. But, even when historical default data is scarce or unavailable, it is often possible to establish a formal link between a bank's internal ratings and external agency ratings. Through this link, which is

[2] Anecdotal evidence suggests that the Great Depression as a central stress scenario appears to be gaining popularity in the industry. 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 its capital position.

commonly referred to as "mapping",[3] banks can employ the default history of external ratings for internal risk assessment purposes. As a result, if mapping is properly implemented, our approach and findings based on corporate bond defaults could also find application in banks' corporate loan portfolios.

In this work, we compare our credit loss measures with those of the internal rating based approach (IRB) in Basel II, the new capital adequacy framework for banks which is in the process of being adopted, according to a recent IMF survey (Caruana and Narain, 2008), in about 100 countries worldwide. We find that our credit risk capital may differ substantially from Basel II and, depending or credit rating and maturity, may be below or above the regulatory level.

The paper is organised as follows. In Section 2 we present our model. Section 3 is a description of our results. Section 4 concludes the paper.

2. The model

The economic capital to be allocated to a credit exposure held by a buy and hold investor can be defined as the difference between the exposure's expected default loss in a downturn and the exposure's long term (i.e. unconditional) average default loss. Credit risk regulatory capital in banks derived under the Internal Rating Based (IRB) approach in Basel II is based on the same idea.[4] In this set-up average losses do not enter the capital definition as long as the firm sets aside provisions to match them. In this sense, credit risk capital is commonly referred to as the "unexpected" loss of default. The default loss, whether downturn or average, is the product of the probability of default and the loss given default, which is given by 1 minus the recovery rate. Both, probability of default and recovery rate depend on the business cycle and tend to be inversely related.

[3] Mapping is one of the techniques for the calculation of default probability of individual corporate, sovereign and bank exposures allowed by Basel II: "Banks may associate or map their internal grades to the scale used by an external credit assessment institution or similar institution and then attribute the default rate observed for the external institution's grades to the bank's grades. Mappings must be based on a comparison of internal rating criteria to the criteria used by the external institution and on a comparison of the internal and external ratings of any common borrowers" (BCBS 2006, p. 102, paragraph 462).
[4] For a detailed description and an assessment of the IRB see, for example, Varotto (2008).

Figure 1 shows Moody's corporate bond default and recovery data between 1982 to 2007. The negative correlation in this period is particularly strong and equals –81.9%. This strong relation will inform our choice of the appropriate default and recovery rate in a downturn, when implementing the model presented in this Section.

Default loss, average and downturn, is computed by applying the simple methodology of EGAM. To define an appropriate downturn scenario the 99.5% or 99.9% quantiles of the 1-year loss distribution are often used when modelling credit risk.[5] These quantiles imply scenarios that occur once every 200 and 1,000 years respectively. But, such long credit histories are simply not available. Researchers normally circumvent the problem by assuming a distribution for the portfolio credit loss (e.g. the KMV model) or for the latent factors (e.g. the CreditMetrics model) or explicit risk factors (e.g. the McKinsey model) that influence such loss.[6,7] Instead, we employ the worst loss scenario produced with our historical default data. The advantage of doing so is twofold. First, we can employ a fairly long default history for individual ratings, which allows us to take into account several business cycles, including the Great Depression period (see Figure 2). Second, we prefer not to make any distributional assumption as this is always a subjective choice and results may be highly sensitive to it, especially when considering extreme events far into the tails of the distribution.

To obtain worst case and average default loss for a corporate exposure (bond or loan), we first determine its price V with the risk neutral valuation in EGAM. The loss will then be,

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

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[5] For instance, the IRB is based on a 99.9% confidence level, while Solvency II, the proposed regulatory framework for European insurance companies, advocates the use of a 99.5% level (see Basel Committee 2006 and CEIOPS 2007).

[6] Another alternative would be to bootstrap the empirical loss distribution from disaggregate (i.e. exposure level) historical default data as illustrated in Carey (1998) and Jacobson et al (2006). This approach would not be feasible with our data sample as we only have aggregate annual default rates for each of Moody's credit rating.

[7] For a comparative description of KMV, CreditMetrics and the McKinsey model see Crouhy, Galai and Mark (2000).

where G is the price of a risk free exposure with the same cash flows as V and i denotes worst case (W) or average (A). Under risk neutrality, today's price (time zero) of a corporate exposure that matures in n years can be calculated with the following iterative expressions,

$$V_{0,n,i} = \frac{aP_{1,i} + (C + V_{1,n})(1 - P_{1,i})}{1 + r_1} \tag{2}$$

with,

$$V_{q,n,i} = \frac{aP_{q+1,i} + (C + V_{q+1,n})(1 - P_{q+1,i})}{1 + f_{q,1}} \quad \text{for } q = 1, \ldots, n-1 \tag{3}$$

where C is the interest payment, a is the recovery rate, $P_{t,i}$ is the (worst case or average) probability of bankruptcy in period t conditional on no bankruptcy in an early period, r_t is the risk free zero-coupon spot rate for maturity t, $f_{q,1}$ is the one-year zero-coupon risk free forward rate at time s, and $V_{n,n}$ is the par value of the exposure which is set to 1.[8] Historical default and recovery rates are obtained from Moody's (Emery et al, 2008). Note that in the above equations the default probabilities are not risk neutral but "physical" unlike in conventional risk neutral pricing. This is because with the EGAM valuation approach the objective is not to produce actual bond spreads. Instead, the procedure generates prices that only reflect expected default loss (average or worst case), without any tax, liquidity or risk premia. This way, pricing factors that are unrelated to the expected loss from default events, and as a result are not relevant for buy and hold investors, are filtered out. Our exclusion of the liquidity component of the spread[9] may appear contentious in the current climate, where illiquidity has undoubtedly caused substantial damage to the banking sector and beyond. However, a buy and hold investor, that is an investor who is committed to keep an asset until maturity, is not affected by the

[8] An implicit assumption in this formulation is that the recovery rate is defined as a percentage of the par value of the bond.

[9] See Perraudin and Taylor (2003) for an assessment of the liquidity component of corporate bond spreads within the EGAM framework.

liquidity of the market for that asset. Indeed, he is exclusively subject to the risk of not receiving interest and principal payments which materializes only if the borrower defaults.

To implement pricing equations (2) and (3) we need to derive the marginal default probabilities $P_{t,i}$. To do so EGAM employ a matrix of rating migration probabilities and assume that the transition process is an time homogeneous Markov chain. Then, for a given rating g and t years to maturity, the marginal default probability can be calculated as,

$$P_{g,t,i} = \frac{CP_{g,t,i} - CP_{g,t-1,i}}{1 - CP_{g,t-1,i}} \text{ for } t = 2,\dots,n \tag{4}$$

where $CP_{g,v}$ is the cumulative default probability for rating *g* extracted from the default column of the v-year transition matrix. The v-year matrix, under time homogeneity, is in turn obtained by multiplying the one-year average transition matrix by itself v times. Note that for t equal to 1, $P_{g,1} = CP_{g,1}$.

However, time homogeneity, which implies that the one-year transition matrix remains constant over time, is clearly only an approximation and may lead to large errors when employed to compute cumulative default rates over long periods (see Bluhm and Overbeck 2007). Therefore, we depart from the assumption of homogeneity and postulate that the downturn transition process is an heterogeneous Markov chain. This assumption is not uncommon. For example, it is employed in CreditPortfolioView, a credit risk model proposed by McKinsey consulting.[10] Also, Bluhm and Overbeck (2007) show how heterogeneous Markov chains can successfully be used to fit the term structure of default rates. The implication of this assumption is that transition matrices are now allowed to vary from year to year. For example, the v-year transition matrix over the period $(s, s+v-1)$ can be computed as,

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

$$M_{s,v} = \prod_{t=s}^{s+v-1} M_t \tag{5}$$

where M_t is the one-year transition matrix at time t. Then, the worst case default loss for an exposure with maturity n and rating g will simply be the largest loss produced by such exposure in any n-year period in the sample. The average loss will be the average of the losses across all n-year periods in the sample. More formally,

$$L_W = \max_s \left(1 - \frac{V(s)}{G}\right) \tag{6}$$

$$L_A = \frac{1}{N-n+1} \sum_{s=1}^{N-n+1} \left(1 - \frac{V(s)}{G}\right) \tag{7}$$

where N is the number of years in our 1920-2007 sample. We should point out, that to simplify the exposition and notation, worst case and average default rates in equations (2) and (3) are not, strictly speaking, "worst case" and "average" on an individual basis. Rather, they denote the default rates in the worst case and average periods respectively. Indeed, in the worst case period, for instance, some default rates, although necessarily not all, may be lower than those in other periods.

The practical implementation of the above procedure requires annual transition matrices over the whole sample period. These are not available, neither can they be reliably estimated prior to 1970 due to the paucity of the data (see Nickell et al 2000). However, annual default rates for each rating category going back to 1920 are indeed obtainable. Then, a simple way to derive time dependent transition matrices back to 1920 would be to replace the default probabilities in the 1920-2007 average matrix with those observed each year in the sample period. Of course, upon changing default probabilities in the average matrix, one should also adjust the non-default probabilities in the original matrix in order to maintain its internal consistency. So, the generic v-year transition matrix would be,

$$M_{s,v} = \prod_{t=s}^{s+v} \left[M_{ND,t} \vdots M_{D,t} \right] \tag{8}$$

where, $M_{D,t}$ is the default vector which includes the default probabilities (for all ratings) observed in year t. $M_{ND,t}$ is the 1920-2007 average transition matrix with the exclusion of the default vector (i.e. the last column), and probabilities in the main diagonal (i.e. the probabilities that indicate the likelihood of retaining the initial rating) adjusted so that the sum of each row of the modified transition matrix $\left[M_{ND,t} \vdots M_{D,t} \right]$ is 1.[11]

It may be argued that using the 1920-2007 average one-year transition matrix for the non-default transition probabilities (i.e. for the block matrix $M_{ND,t}$) may lead to underestimation of the expected default loss in the downturn scenario because downgrade probabilities may be higher in stress periods than during average periods. We address this point by testing the sensitivity of our results when instead of using the average 1920-2007 matrix, we derive $M_{ND,t}$ with transition matrices estimated in recession periods. Specifically, we use the trough transition matrix in Nickell et al (2000) based on Moody's data for the period 1970-1997, which we reproduce in Panel B of Table 1, and the recession transition matrix in Bangia et al (2002) based on Standard&Poor's 1981-1998 data (Table 1, Panel C). Interestingly, the default rates in the downturn matrices in Panel B and C are higher than in the average matrix in Panel A but only for speculative grade assets. With the exception of AAA, which exhibits zero defaults regardless, all the investment grade ratings in Panel B and the top two in Panel C have a lower default rate

[11] The adjustment consists of lowering the probabilities in the main diagonal. This is the most conservative approach, that is the one that produces, in most cases, the highest downturn credit losses. The alternative would be to decrease all non-default probabilities proportionally to their value. This, which is a popular procedure to re-scale transition probabilities after the exclusion of withdrawn ratings (see, for example, Bangia et al 2002) would be inappropriate in this context as it would lead to downgrade probabilities that are lower in the worst case scenario than on the average scenario, which is difficult to justify. As a robustness check we have also estimated worst case default losses with the latter method and the difference in our results is, however, negligible.

than in the average 1920-2007 matrix. This reflects the influence on long term averages of the Great Depression which was characterised by abnormally high default rates especially for companies with a high rating.

2.1 Regulatory capital

The above procedure allows us to obtain the worst case and average default loss of an individual exposure with a given rating, recovery rate and maturity. Economic capital is then the difference between these two measures. Under the IRB, regulatory capital is determined in a similar fashion. Specifically, the IRB capital requirement K for a wholesale corporate exposure i with rating g will be,

$$K_i = CF \cdot MA_i \cdot \left[(1-a_i)P_{g,1,W} - (1-a_i)P_{g,1,A}\right] \quad (9)$$

where *CF* is a calibration factor introduced to "broadly maintain the aggregate level of [minimum capital] requirements" to the pre-Basel II level;[12] MA_i is a "maturity adjustment" employed to rescale the capital charge to make it an increasing function of the exposure's duration. As for economic capital, the core element of IRB regulatory capital is the $L_W - L_A$ difference expressed in the square brackets in (9). It should be noted that economic capital, as derived in the previous Section, already takes into account maturity effects through the term structure of default rates employed in (2) and (3). Therefore, a "maturity adjustment" for our economic capital calculations is unnecessary.

In the IRB, the one-year worst case default probability (termed "downturn" default probability in the Basel II document) is defined as,

$$P_{g,1,W} = \Phi\left(\frac{\Phi^{-1}\left(P_{g,1}\right) + \Phi^{-1}(99.9\%)\sqrt{R_g}}{\sqrt{1-R_g}}\right) \quad (10)$$

[12] Basel Committee (2006), page 4, paragraph 14.

where Φ is the cumulative standard normal and $\sqrt{R_g}$ is the correlation between the assets of the borrower and a systematic risk factor. The systematic factor is assumed to be unique and common across all the exposures in the portfolio. The correlation $\sqrt{R_g}$ is deterministically related to the probability of default associated with borrower's credit rating.[13] For more details about the above formulation see, for example, Resti and Sironi (2007).

2.2 Default loss sensitivity to interest rates

The default loss in equation (1) (whether worst case or average) is clearly a function of interest rates. The loss depends on the ratio V_i/G and both the corporate exposure price V_i and the riskless asset price G depend on interest rates. Since by construction both exposures have the same cash flows, the sensitivity of the riskless asset to interest rates (that is, its duration) is necessarily higher than that of the corporate exposure. In fact duration is inversely related to the yield of the exposure, and the yield of the riskless asset must be lower than the corporate exposure's yield. It follows that as interest rates increase the ratio V_i/G also increases because G will fall more than V_i. As a result, the default loss will fall. When implementing the model introduced in the previous Section we shall take a conservative approach whereby interest rates are set to zero and hence default losses are maximised.

3. Results

In this Section we present our findings on default loss, economic and regulatory capital for plain vanilla corporate bond exposures. The bonds are interest bearing. As in EGAM, the coupon is determined endogenously for every credit rating in such a way that the

[13] Asset correlation for small and medium enterprises in the IRB also varies in relation to the size of the borrower. For simplicity, we shall assume that our exposures are large corporates for which asset correlation is not dependent on firm size. (See Basel Committee 2006, paragraphs 272 and 273).

price of a 10 year bond with that rating equals the bond's par value.[14, 15] In Table 2 we show worst case and average default loss as well as economic capital for AAA to single-B ratings, several maturities and for different transition assumptions. The CCC rating was dropped because it is often poorly populated and the resulting small sample bias in its estimated default rates is likely to be substantial.[16] For simplicity, we shall report our results by using Standard and Poor's letter ratings (AAA, AA, A, BBB, BB, B and CCC) irrespective of the source of default and transition data employed in our calculations. The average loss is obtained by assuming a mean recovery rate of 46%. The worst case loss, given the highly negative correlation between default rates and recovery rates documented in Figure 1, was computed by assuming a conservative recovery rate of 20%.[17] In Panel A of Table 2, average default losses are produced with the average transition matrix estimated by Moody's over the 1920-2007 period. Worst case losses are the largest default losses in the sample period derived with the same transition matrix but adjusted as described in the model Section. Several patterns are clearly discernible. As is to be expected, both losses as well as economic capital are increasing as the credit rating deteriorates. All three also increase with maturity. However, while the trend for economic capital is broadly upward, there are instances for intermediate maturities not reported in the Table in which it falls as tenure increases. Since capital is the difference between worst case loss and average loss, its relationship with maturity will depend on the relative change of each loss as tenure changes. Although typically the changes in worst case loss dominate those in average loss, there may be exceptions. The economic intuition is that although total default risk increases with maturity, the proportion of it that is expected (and set aside as general loss provisions by the investor) may change with maturity. This

[14] Coupon payments are determined by assuming the Moody's average transition matrix over the period 1920-2007 and a recovery rate of 40%. To make the comparison of results more meaningful, the coupon for each rating is kept constant when different recovery rates and transition matrices are used.

[15] As a robustness check we have used alternative coupon assumptions and found only second order effects in our results. Specifically, coupons were also implicitly determined in order to set to par the price of bonds with maturities spanning the whole spectrum considered in this study, i.e. from 1 to 20 years.

[16] For instance, on average there were 7.2 issuers rated CCC 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 instance between 1981 to 1986, a period characterised by default rates across all rated bonds close to the long term historical average, the 1-year default rates for CCC bonds as reported by Moody's were 33.3%, 0%, 25%, 40%, 100%, 0%, 26.7%.

[17] Recovery rates for senior unsecured bonds found in Emery et al (2008) for the period 1982-2007 range from a minimum value of 21.45% in 2001 to a maximum of 62.75% in 1996. The average recovery is 45.9%.

simply follows from default loss uncertainty in that a higher expectation of default loss does not necessarily translate in a higher actual loss. This intuition is confirmed by the figures in the Table. Not only is the ratio between average loss and worst case loss not stable but it also moves in a characteristic way showing a positive trend as maturity increases and credit quality falls (with only few inversions).

From the 88 year corporate bond default history used to derive our results we can see that (Panel A) the worst case loss, average loss and capital associated with a AAA asset over a 1 year period are all 0%. Indeed, no bond rated AAA by Moody's at the beginning of any year between 1920 and 2007 has ever defaulted over the next 12 months. On the other hand, when looking at single-B rated bonds the three quantities are markedly higher at 15.9%, 1.93% and 13.97% respectively with the majority of the default loss being unexpected, as the level of economic capital indicates. When the holding period of the investment is extended to 20 years, default losses and economic capital all move up to 4.17%, 0.88% and 3.29% for AAA and at 54.98%, 26.58% and 28.40% for single B. Now, however, the default loss that is unexpected plays a minor role.

In Panel B of Table 2 average losses are obtained with the 1970-1997 average one-year transition matrix estimated by Nickell et al (2000). The new average transition matrix appears to produce smaller average expected losses. On the other hand, worst case losses, generated with the trough transition matrix estimated by the same authors during trough business cycle periods between 1970 and 1997, are very similar to those in Panel A. The difference in economic capital between Panel A and B is also small and does not reveal any specific pattern. Finally, in Panel C of Table 2 we compute average and worst case losses with the unconditional and recession transition matrices estimated by Bangia et al (2002). As before, expected losses are generally lower than in Panel A. On the contrary, worst case losses and economic capital in Panel C are generally higher than in Panel A. This may be a consequence of the different sample period (1981-1998) as well as data source (S&P's) used by Bangia et al (2002).[18]

[18] It should be noted that the three 1-year matrices, when adjusted as in (8) for the purpose of our analysis, differ only in their transition probabilities to the non-default states (i.e. AAA to single-B). 1-year default

To present our default loss findings in a more familiar form we derive the implied credit spreads associated with each loss for every maturity/rating combination. The resulting term structures of credit spreads under the average and worst case scenarios are reported in Figure 3. The spreads have been obtained with the Nelson and Siegel (1987) method extended as in Svensson (1995), which allows us to estimate zero coupon yields and hence zero coupon spreads. Perhaps, the most noticeable feature of the estimated spreads is that those under the worst case scenario are by and large downward sloping with the exception of AAA spreads. The downward pattern is the result of the short duration of crisis periods. As it can be seen in Figure 2 even during the most serious trough in the 1930s, high default rates are not persistent. The peak in 1933 (with a default rate of 8.40%) is followed by a sharp drop in 1934 (3.45%) with default rates reverting back to a level close to the 1920-2007 average (1.08%) in 1936 (1.64%). This implies that worst case losses will fall over time because, if a firm survives the crisis, it will face substantially lower default risk in subsequent periods. This argument does not apply to AAA as its 1-year default rate is unaffected by crisis periods and has always remained equal to zero since 1920. As a result, AAA does not suffer from the initial abnormal increase in defaults observed in all other rating categories, which is responsible for their downward sloping worst case loss. Instead, AAA exhibits a worst case loss that, like the AAA average loss, is always increasing. AAA worst case loss however is larger than AAA average loss for maturities of 2 years or longer. This results from "indirect" migration to default that follows after a downgrade to AA or lower rating after the first year and from the higher annual default rates for all non-AAA ratings during crisis periods.

We now proceed to compare our economic capital results with the capital requirements derived under the IRB in Basel II. For both economic and regulatory capital we use the

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probabilities, on the other hand, are common since those of the original matrices are replaced with actual default rates observed over the 1920-2007 sample period. The implication is that the default losses (and as a result economic capital) for the one-year holding period are identical across the three Panels in Table 2 because they only depend on 1-year default probabilities. On the other hand, default losses of longer holding periods, being influenced by cumulative default rates which are calculated by employing non-default transition probabilities (as per equation 8), will normally differ.

same default data. However, unlike for economic capital where recovery rates vary for average loss (46% recovery) and worst case loss (20% recovery), IRB capital is calculated by retaining the same recovery rate in both the average and downturn scenario (see equation 9). So, for the IRB capital we shall use a common 20% recovery. It should be noted that this approach in not as conservative as the one adopted for economic capital and it would lead, all else equal, to economic capital being larger than its regulatory counterpart.[19] In fact, we shall see, that the IRB specification more than compensates for this initial "disadvantage" and will yield capital levels that are mostly higher than our economic capital model's. Table 3 shows the ratios of economic to regulatory capital for various exposures. For this comparison economic capital is computed in two ways. First, it is derived as described in Section 2 by subtracting worst case loss from average loss. Results derived with this approach are reported under the heading "Average Economic Capital". However, investors may also be interested in the "Maximum Economic Capital" that an exposure may attract when using current, rather than long-term average default loss estimates. The maximum will be reached in a business cycle peak when the distance between (current) expected loss and worst case loss is highest. This may be a useful benchmark as it is inherently counter-cyclical, as it would encourage banks to raise safety capital buffers during good times when capital is widely and cheaply available. This in turn could help prevent the rushed and expensive bank capital injections that have been witnessed in the current turmoil. To derive "maximum" economic capital we compute the difference between worst case and "best case" loss, that is the lowest default loss over the whole sample period estimated using peak periods default rates and a 60% recovery rate. In addition to the 1920-2007 average transition matrix, in order to account for the different upgrade and downgrade probabilities in peak periods relative to the average case, we also compute best case loss with the transition matrices estimated in peak/expansionary periods by Nickell et al (2000) and Bangia et al (2002).

The main finding in Table 3 is that regulatory and economic capital often diverge substantially. The discrepancy between the two varies considerably across maturities and

[19] This can be easily seen from equation (9). If the recovery rate for the average loss is higher than for the downturn loss, regulatory capital would increase.

credit ratings. Regulatory capital appears to be more conservative than average economic capital for all except very low quality assets or assets with long maturity (i.e. in excess of 10 years). For speculative grade assets and long term maturities the results are more ambiguous. Economic capital is largest in relative terms at 20 year maturity, the longest considered. This is because IRB capital is designed to increase up to a 5 year (effective) maturity[20] and remains constant thereafter, while economic capital as shown in Table 2 keeps increasing to the 20 year mark (with few minor drops at intermediate maturities). The comparison between maximum economic capital and regulatory capital yields similar results, but, as it is to be expected, ratios are higher. The three panels, obtained as before with alternative transition matrices, show very similar patters except for AA and A rated assets whose ratios in Panel B and C are much larger than those in Panel A. This may come as a surprise given that the economic capital derived with the same transition matrices and reported in Panel A, B and C of Table 2 are similar (except for the capital at 20 year maturity in Panel C). The reason for the higher AA and A ratios is that regulatory capital falls markedly when using the transition matrices employed in Panel B and C. This happens because regulatory capital for all maturities is based on one-year average default rates (scaled up for longer maturities through the maturity adjustment as shown in (9)). Since AA and A one-year default rates are much lower in Panel B and C's transition matrices than in the Panel A's matrix, it follows that the regulatory capital they produce should also be noticeably lower.

As a final exercise we investigate how the IRB approach could be recalibrated to make it consistent with Moody's corporate default data incorporated in our economic capital estimates. To do so, we have adjusted either the confidence level or the level of asset correlation adopted in the IRB framework. Average results across the three transition matrices employed to obtain (average) economic capital are reported in Figures 4 to 9. In line with our previous observations, the implied confidence level and asset correlation are both rating and maturity dependent. AAA exposures exhibit the lowest implied confidence level and asset correlation and the largest discrepancy in defect of the

[20] 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).

regulatory levels (see Figures 4 and 7 respectively). This appears to be the case across all maturities. The implied confidence level for AAA falls from the 99.9% required in the IRB to 81.4% for assets with a residual life of 1 year, and peaks at 99.87% at 20 year maturity. AAA implied asset correlation falls from a regulatory level of 24%[21] to one between 0 and 22.13% depending on maturity. The largest discrepancy in excess of the regulatory benchmark are obtained by single-A exposures with a confidence level of 99.98% and a correlation of 38.45%, up 14.69% from the IRB level, both at a 20 year maturity (Figures 5 and 7).

4. Conclusion

In this paper, we describe a simple method to determine ratings-based economic capital allocations for credit risk exposures held by a buy-and-hold investor. The novelty of our approach is that it does not rely on market prices, which may become uninformative especially in periods of protracted market illiquidity as seen during the current financial crisis. In addition our method does not require any distributional assumption nor computer simulations as it only employs the default and transition history of individual credit ratings. Computer simulations and/or distributional assumptions are normally used within credit risk models to produce transaction level risk measures in the form of marginal VaRs. These, however, can be computationally intensive and may be unstable over time. Regulatory capital under the new IRB in Basel II, on the other hand, is based on a simplified approach which circumvents the use of simulations and the specification of complex dependence structures but still relies on the normality of a systematic factor. In this paper, we retain the simplicity of the IRB while removing its dependence on normality which may potentially cause large errors (see Tarashev and Zhu, 2008). Further, we do away with the use of explicit confidence levels which imply observation periods far longer than any currently available default and transition history. Instead, by using observed default data we provide a "reality check" that ensures that our estimates

[21] The correlation under the IRB depends on the type of exposure (wholesale vs retail) and on the specific value of the probability of default assigned to the rating. For wholesale exposures and a 1-year default probability of zero (which is the value assigned by Moody's to Aaa in their 1920-2007 average transition matrix) the regulatory asset correlation would be 24%.

of economic capital have a clear economic meaning and a documented possibility of occurrence. With default histories stretching a period of almost 90 years, including severe downturns and the Great Depression, we ensure that large negative swings in exposure and portfolio value are properly accounted for. Our approach can in principle be extended to corporate exposures with short rating and default histories provided that a sensible mapping to agency ratings can be established. When comparing economic capital with regulatory capital we find substantial discrepancies which vary across ratings and maturities. Our analysis indicates that regulatory capital tends to be more conservative than economic capital, often markedly so. Exceptions are very low quality or long maturity assets (i.e. over 10 years). Robustness checks conducted by employing rating transition matrices estimated from different data sources confirm our findings.

Our conclusions appear to be at odds with overwhelming evidence from the markets that banks, regulated under Basel II, were not sufficiently capitalised to withstand the current crisis. This problem was so acute that in several countries, including the US, UK, Germany, France, Switzerland and the Netherlands, the local governments have been planning or have already implemented equity capital injections in key banks. Can this be taken as evidence that Basel II produces inadequate capital levels? Before drawing far reaching conclusions, several considerations are in order. First, Basel II was not fully implemented by all the above countries at the onset of the crisis. Most notably, US core banks will only be required to apply the IRB from 2009 (see GAO 2008). Second, Basel II distinguishes between capital for buy and hold exposures (credit risk capital) and capital to be set aside against the risks in securities trading (market risk capital). The rules for the latter type of capital were introduced in 1996 (see Basel Committee, 1996), partially revised in 2005 (see Basel Committee 2005) and left substantially unchanged when incorporated in the final Basel II document released in 2006. Collateralised debt obligations and mortgage backed securities, considered by several commentators as being the trigger of, and as playing a crucial role in, the current crisis, are treated as market risk instruments and hence are not subject to the IRB approach, which is the main innovation introduce by Basel II in its Pillar 1. Instead, their regulatory capital is determined with value-at-risk models that measure risk over a 10 day period and with a 99% confidence level (unlike in the IRB where the investment horizon is set at 1 year and the confidence level is 99.9%). The rationale behind the 10 day horizon is that banks should be able to trade out of their market risk exposures quickly and hence stop losses in the event of negative market movements. In the case of CDOs and MBSs this assumption turned out to be severely flawed. As markets became illiquid, offloading those securities at a reasonable price (or at any price) could not be achieved so promptly. The large write-downs that followed and the ensuing lack of confidence in the stability of the banking system led to a deterioration of the crisis which culminated in October 2008 with a dramatic fall in stock markets around the world. Interestingly, in a consultative document issued in 2007 and subsequently revised in 2008,[22] the Basel Committee proposed the introduction of a new incremental capital charge for market risk instruments. Such a charge, which is to be added to the market risk capital derived with the old rules - and is scheduled to become effective from the beginning of 2010 - will have to be estimated on the basis on a 1-year holding period and a 99.9% confidence level as in the IRB. Whether the new charge, more IRB like, would have actually produced a capital buffer sufficient to shield banks against the current turmoil remains an open question. Another critical factor behind the current crisis appears to be the liquidity of bank funding and, more specifically, banks' excessive reliance on short term and volatile borrowing from the interbank market. So, while Basel II's main focus is on the asset side of the balance sheet, a non trivial part of the problem in the current crisis came from the liability side. Therefore, it appears that it is questionable whether the current crisis may be used as a final verdict against the novel features introduced by Pillar 1 in Basel II, namely the IRB and operational risk capital. Instead, one may argue that greater attention to how banks fund their business (money markets versus deposits), more conservative capital requirements for market risk instruments and counter-cyclical capital rules, of which a simple implementation is discussed in this work, may prove to be effective ways to redress the main shortcomings of current regulation.

[22] See Basel Committee (2007, 2008).

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Table 1: Average and Downturn Transition Matrices

Panel A: Moody's average transition matrix, 1920-2007

	Aaa	Aa	A	Baa	Ba	B	Caa-C	D
Aaa	91.1	7.8	0.9	0.2	0.0	0.0	0.0	0.0
Aa	1.3	90.7	6.9	0.7	0.2	0.0	0.0	0.1
A	0.1	3.1	90.2	5.6	0.7	0.1	0.0	0.1
Baa	0.0	0.3	5.0	87.8	5.5	0.8	0.2	0.3
Ba	0.0	0.1	0.5	6.6	82.7	7.8	0.7	1.5
B	0.0	0.1	0.2	0.7	7.1	81.2	6.3	4.4
Caa-C	0.0	0.0	0.1	0.1	0.8	6.9	73.8	18.2

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

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

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

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

Table 2: Worst Case Default Loss, Average Default Loss and Economic Capital

All figures are in percent

Maturity	AAA	AA	A	BBB	BB	B
	Panel A: Moody's average transition matrix, 1920-2007					
	Worst Case Loss					
1	0.00	0.67	1.37	1.58	8.92	15.90
2	0.07	0.71	1.78	2.61	12.92	22.02
3	0.14	1.41	2.18	4.10	14.85	27.55
5	0.39	2.07	3.52	6.72	19.33	34.96
10	1.40	3.73	5.91	11.43	24.24	45.95
20	4.17	7.48	11.57	19.89	33.60	54.98
	Average Loss					
1	0.00	0.03	0.05	0.15	0.57	1.93
2	0.00	0.07	0.11	0.33	1.25	3.97
3	0.01	0.10	0.18	0.56	2.02	6.02
5	0.03	0.20	0.38	1.14	3.76	9.92
10	0.18	0.58	1.18	3.15	8.43	17.63
20	0.88	1.99	3.74	7.86	15.90	26.58
	Economic Capital					
1	0.00	0.64	1.32	1.43	8.35	13.97
2	0.06	0.65	1.67	2.28	11.67	18.04
3	0.13	1.31	2.00	3.54	12.84	21.53
5	0.35	1.87	3.15	5.57	15.57	25.05
10	1.22	3.15	4.73	8.28	15.81	28.32
20	3.29	5.49	7.83	12.03	17.71	28.40
	Panel B: Nickell et al's transition matrices, 1970-1997					
	Worst Case Loss					
1	0.00	0.67	1.37	1.58	8.92	15.90
2	0.07	0.74	1.78	2.55	12.95	21.79
3	0.15	1.46	2.18	3.96	14.91	26.33
5	0.42	2.17	3.50	6.47	19.25	32.66
10	1.47	3.72	5.46	10.72	23.46	42.37
20	3.99	6.84	10.03	17.72	31.76	51.04
	Average Loss					
1	0.00	0.03	0.05	0.15	0.57	1.93
2	0.00	0.06	0.10	0.32	1.21	3.77
3	0.01	0.10	0.17	0.52	1.89	5.52
5	0.03	0.18	0.33	0.99	3.38	8.74
10	0.14	0.48	0.93	2.48	7.22	15.04
20	0.62	1.49	2.71	5.87	13.34	22.48
	Economic Capital					
1	0.00	0.64	1.32	1.43	8.35	13.97
2	0.07	0.67	1.68	2.23	11.74	18.02
3	0.14	1.36	2.01	3.44	13.02	20.81
5	0.39	1.99	3.17	5.48	15.87	23.92
10	1.33	3.24	4.53	8.23	16.24	27.34
20	3.37	5.35	7.31	11.86	18.42	28.57

Table 2: continued

	Panel C: Bangia et al's transition matrices, 1981-1998					
Maturity	Worst Case Loss					
1	0.00	0.67	1.37	1.58	8.92	15.90
2	0.06	0.74	1.78	2.77	13.21	22.23
3	0.13	1.47	2.20	4.47	15.63	28.77
5	0.37	2.22	3.56	7.32	20.59	37.56
10	1.36	4.25	6.47	13.09	30.70	52.10
20	4.68	9.90	15.14	25.95	43.60	63.15
	Average Loss					
1	0.00	0.03	0.05	0.15	0.57	1.93
2	0.00	0.07	0.11	0.33	1.27	3.86
3	0.01	0.11	0.18	0.56	2.06	5.71
5	0.03	0.21	0.37	1.12	3.79	9.16
10	0.16	0.58	1.15	2.99	8.10	15.85
20	0.73	1.79	3.46	7.10	14.56	23.58
	Economic Capital					
1	0.00	0.64	1.32	1.43	8.35	13.97
2	0.06	0.67	1.68	2.44	11.94	18.38
3	0.12	1.36	2.02	3.91	13.57	23.06
5	0.33	2.01	3.18	6.20	16.80	28.40
10	1.20	3.67	5.32	10.11	22.60	36.25
20	3.94	8.11	11.68	18.85	29.04	39.56

Table 3: Economic to Regulatory Capital Ratios

Maturity	AAA	AA	A	BBB	BB	B
	Panel A: Moody's average transition matrix, 1920-2007					
	With Average Economic Capital					
1	0.0	30.2	54.8	23.7	64.3	73.4
2	3.5	21.5	49.4	30.1	78.8	87.1
3	5.2	33.7	46.2	39.3	77.6	96.5
5	9.7	33.8	51.7	47.5	78.6	99.2
10	31.2	53.3	72.9	66.8	76.3	107.7
20	84.3	92.9	120.7	97.0	85.5	108.0
	With Maximum Economic Capital					
1	0.0	31.6	56.8	26.1	68.7	83.6
2	3.7	23.6	52.6	34.5	87.2	106.3
3	5.6	36.4	50.4	45.5	89.8	123.5
5	10.7	37.4	57.8	57.1	97.4	136.6
10	35.7	63.0	90.6	91.3	115.1	170.1
20	105.7	124.7	174.3	154.5	151.9	194.5
	Panel B: Nickell et al's transition matrices, 1970-1997					
	With Average Economic Capital					
1	0.0	55.6	115.5	50.9	67.8	61.7
2	3.8	37.3	93.1	57.7	83.0	74.1
3	5.6	56.0	82.6	70.5	81.9	80.5
5	10.8	54.7	87.2	80.9	82.9	83.2
10	34.1	83.0	116.1	113.9	81.0	91.8
20	86.4	137.1	187.4	164.0	91.9	96.0
	With Maximum Economic Capital					
1	0.0	58.3	119.7	56.1	72.4	70.2
2	4.0	40.8	98.8	66.0	91.5	89.6
3	6.0	60.1	89.5	81.2	93.9	101.8
5	11.6	59.7	96.2	95.4	100.5	112.9
10	37.7	95.2	139.8	147.6	115.8	139.3
20	101.8	174.1	254.7	240.6	152.0	162.0
	Panel C: Bangia et al's transition matrices, 1981-1998					
	With Average Economic Capital					
1	0.0	55.6	92.5	28.2	75.2	67.9
2	3.2	37.2	77.3	37.5	92.5	82.6
3	4.8	56.0	70.0	49.9	92.7	96.9
5	9.2	55.2	75.3	59.8	94.1	106.3
10	30.9	94.1	117.5	92.1	120.5	130.6
20	101.1	207.8	257.9	171.8	154.8	142.6
	With Maximum Economic Capital					
1	0.0	58.3	95.8	31.0	80.4	77.3
2	3.4	41.0	82.3	42.6	102.4	100.0
3	5.2	60.5	76.3	57.0	106.8	120.9
5	10.0	60.9	84.1	70.5	115.1	139.2
10	34.8	108.6	142.3	118.4	161.7	183.7
20	118.9	251.0	329.8	231.4	223.7	215.9

Figure 1

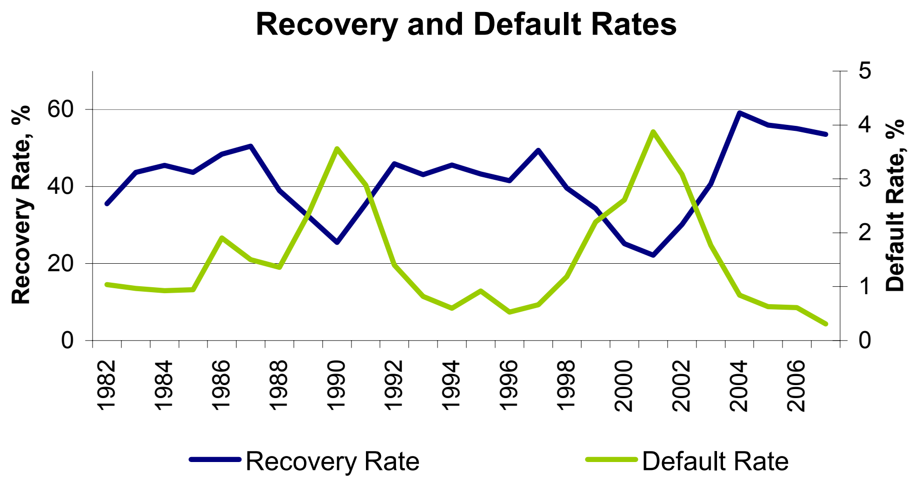

Figure 2

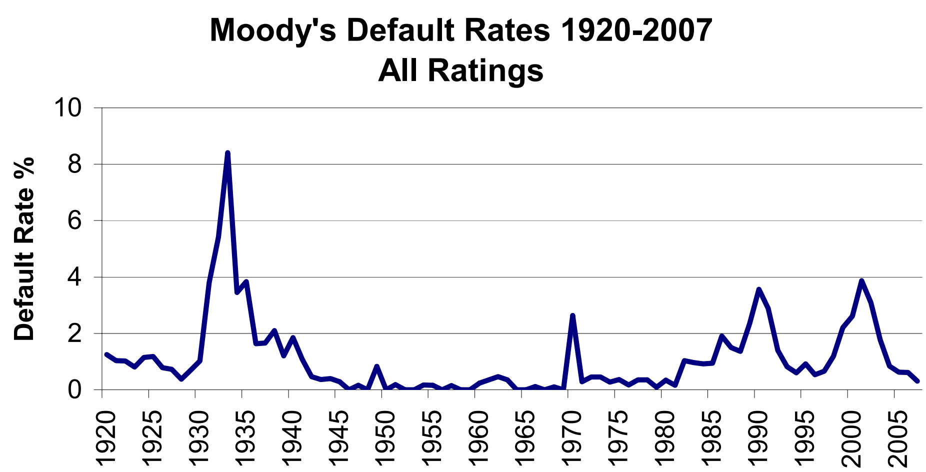

Figure 3

Average and Worst Case Credit Spreads Assuming Risk Neutrality

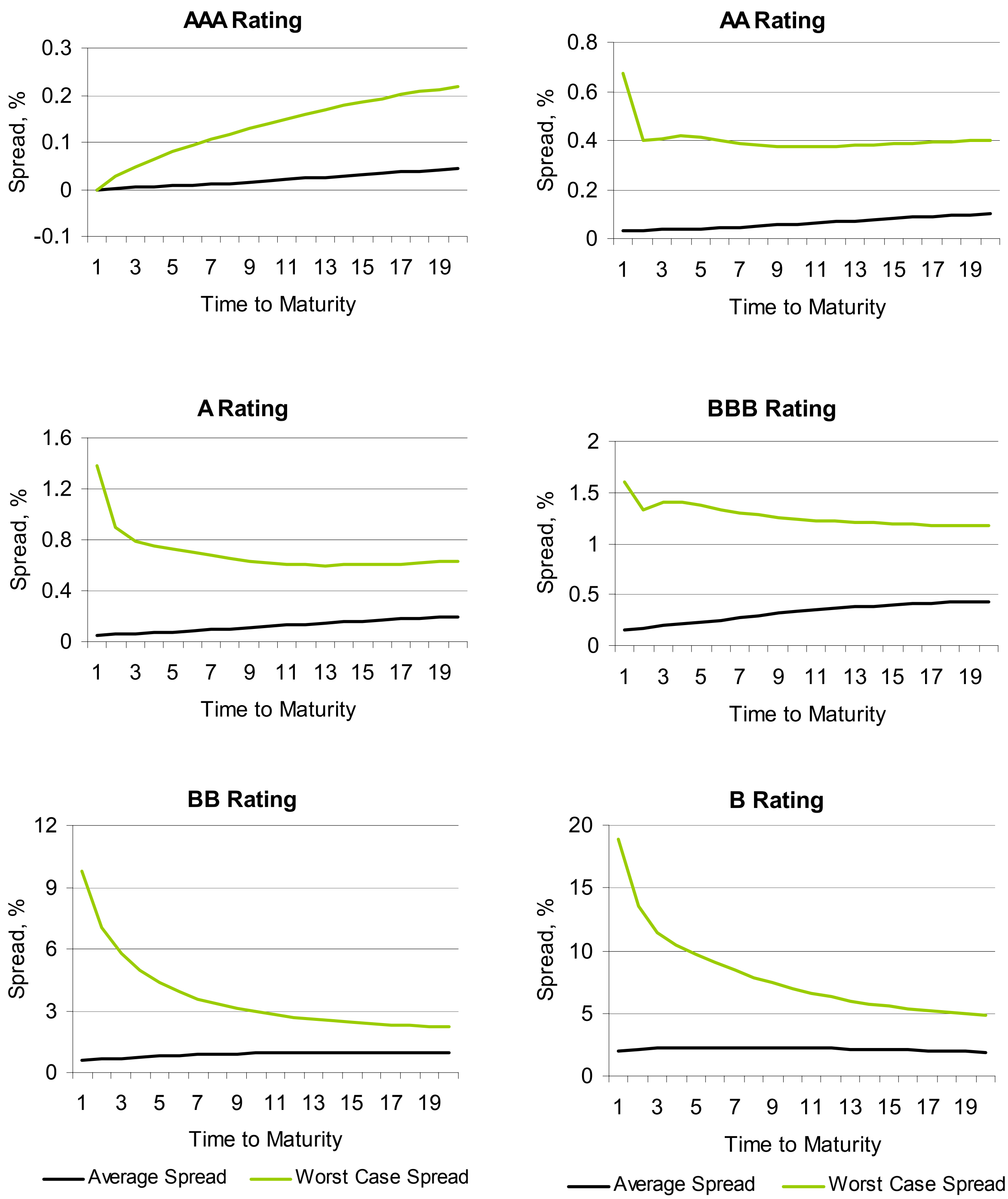

Figure 4

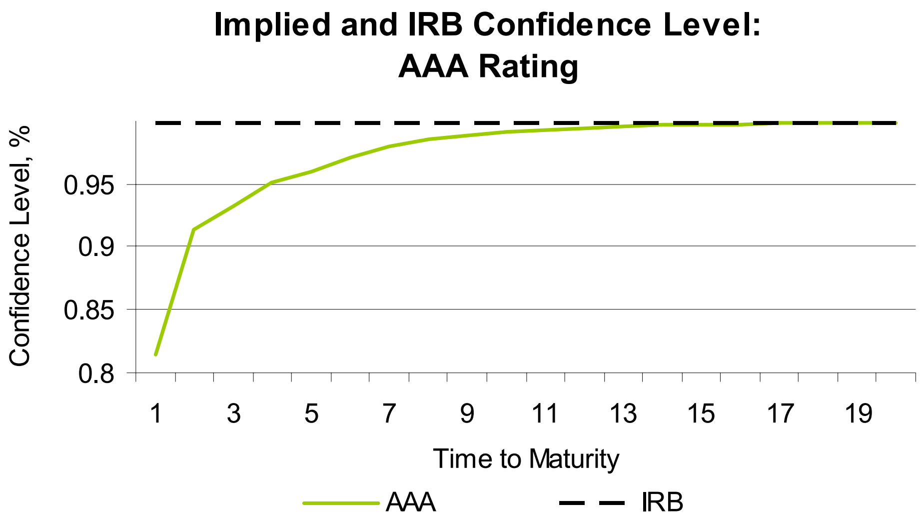

Figure 5

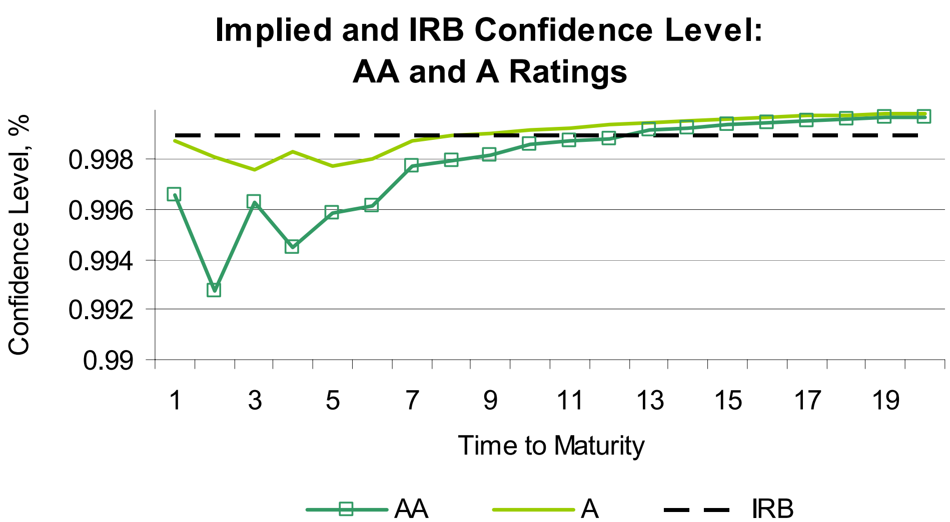

Figure 6

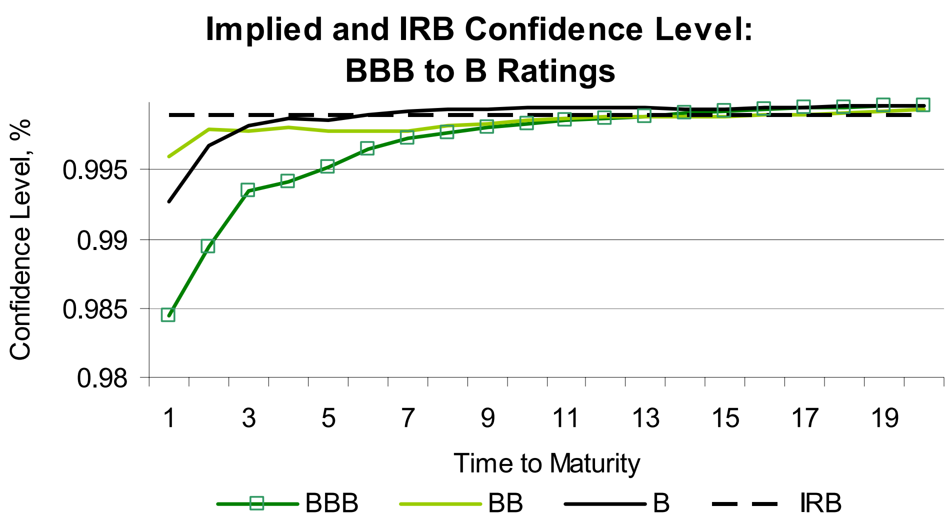

Figure 7

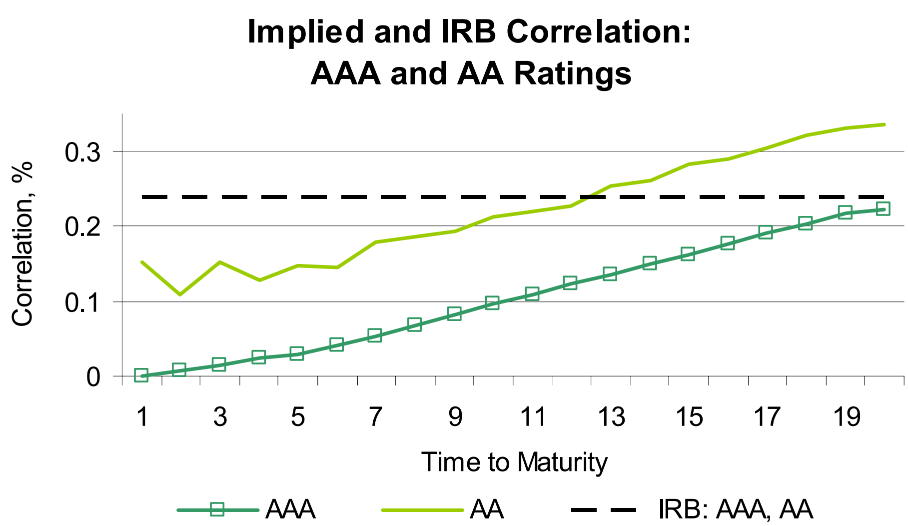

Figure 8

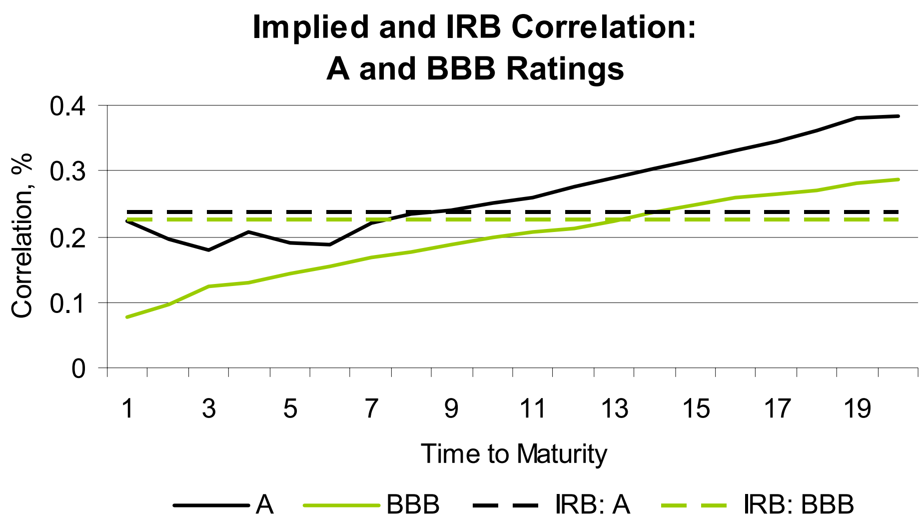

Figure 9