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The impact of downward rating momentum on credit portfolio risk

André Güttler
(European Business School)

Peter Raupach
(Deutsche Bundesbank)

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Editorial Board: Heinz Herrmann
Thilo Liebig
Karl-Heinz Tödter

Deutsche Bundesbank, Wilhelm-Epstein-Strasse 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-1
Telex within Germany 41227, telex from abroad 414431

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax +49 69 9566-3077

Internet http://www.bundesbank.de

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Abstract

Rating downgrades are known to make subsequent downgrades more likely. We analyze the impact of this 'downward momentum' on credit portfolio risk. Using S&P ratings from 1996 to 2005, we estimate a transition matrix that is insensitive to and a second matrix that is sensitive to previous downgrades. We then derive differences between the insensitive portfolio Value-at-Risk (VaR) and the momentum-sensitive VaR. We find realistic scenarios where investors who rely on insensitive transition matrices underestimate the VaR by eight percent of the correct value. The result is relevant for risk managers and regulators since banks neglecting the downward rating momentum might hold insufficient capital.

JEL-Classification: C41, G24, G32

Keywords: Rating drift, Downward momentum, Credit portfolio risk, Value-at-Risk

Non-technical summary

In the analysis of rating transitions, *rating momentum* means that the probabilities of future transitions and defaults do not depend on the current rating only but also on previous transitions. In the case of downgrades, there is much empirical evidence of rating momentum: within a certain rating category, ratings with previous downgrades are more prone to further downgrades and defaults than others. The rating momentum has an impact on the risk of value changes in a bond portfolio: Given two portfolios with equal rating distribution, and given a large share of previously downgraded bonds in the first one but a lower share in the second one, more future defaults and losses through revaluations of downgraded bonds are expected in the first portfolio.

We analyze the impact of the rating momentum on credit portfolio risk with an emphasis on realistic assumptions. Using S&P ratings from 1996 to 2005, we estimate a transition matrix that is sensitive to and a second matrix that is insensitive to previous downgrades. We then apply the matrices to a CreditMetrics®-type portfolio model and calculate differences between the insensitive portfolio Value-at-Risk (VaR) and the momentum-sensitive VaR, which we consider to be the correct one. In doing so, we assume that the portfolio manager accounts for the current ratings of the bonds but not for their momentums, thus choosing some previously downgraded bonds by pure chance. This provides us with a measure for the risk of misperceiving the portfolio VaR.

We find that the momentum-insensitive VaR of 6.7% underestimates the correct sensitive VaR by 0.24% of the portfolio volume (3.5% of the correct VaR), on average. More important, there is substantial fluctuation: Given normal conditions, there is a 5% probability that the insensitive VaR underestimates the correct VaR by more than 0.59% (8.1% of the correct VaR). Given a stressed economy, the misperception can easily reach 1.8% (6.8% of the correct VaR).

The result is relevant for risk managers and regulators since banks neglecting the downward rating momentum might hold insufficient capital.

Nicht technische Zusammenfassung

In der Analyse von Ratingänderungen spricht man von einem *Ratingimpuls* (rating momentum), wenn die Wahrscheinlichkeit zukünftiger Ratingänderungen und Ausfälle nicht nur vom aktuellen Rating, sondern auch von früheren Ratingänderungen abhängt. Für Herabstufungen ist ein Ratingimpuls vielfach empirisch belegt: Innerhalb einer Ratingklasse haben die Anleihen mit vorangegangenen Herabstufungen eine höhere Ausfallwahrscheinlichkeit und eine höhere Wahrscheinlichkeit, herabgestuft zu werden, als solche ohne vorangegangene Herabstufungen. Dieser Ratingimpuls hat einen Einfluss auf das Wertänderungsrisiko eines Anleihenportfolios: Vergleicht man zwei Portfolios mit gleicher Ratingzusammensetzung, von denen das erste einen hohen Anteil zuvor herabgestufter Anleihen hat und das zweite einen geringen, dann sind im ersten Portfolio mehr Ausfälle und Barwertverluste durch die Neubewertung nach Herabstufungen zu erwarten als im zweiten.

Wir messen den Einfluss des Ratingimpulses auf das Kreditportfoliorisiko unter möglichst realistischen Annahmen. Mit Standard-and-Poor's-Daten von 1996 bis 2005 schätzen wir zunächst eine Ratingmigrationsmatrix, die den Ratingimpuls berücksichtigt, und eine Matrix, die den Impuls ignoriert. Anschließend verwenden wir die Matrizen in einem Kreditportfoliomodell vom Typ CreditMetrics® und berechnen Unterschiede zwischen dem Value-at-Risk (VaR) mit und ohne Berücksichtigung des Ratingimpulses, wobei wir ersteren als richtig ansehen. Wir nehmen dabei an, dass der Portfoliomanager das aktuelle Rating, aber nicht den Ratingimpuls beachtet, also rein zufällig einige zuvor herabgestufte Anleihen ausgewählt hat. Wir gewinnen damit ein Risikomaß für die Fehleinschätzung des VaR.

Es zeigt sich, dass ohne Berücksichtigung des Ratingimpulses der VaR von 6,7 % den korrekten VaR mit Ratingimpuls im Mittel um 0,24 % des Portfoliovolumens (3,5 % des richtigen VaR) unterschätzt. Bedeutsamer sind aber die erheblichen Schwankungen: Unter normalen Bedingungen gibt es eine Wahrscheinlichkeit von 5 %, dass der VaR ohne Ratingimpuls den korrekten VaR um mehr als 0,59 % (8,1 % des richtigen VaR) unterschätzt; in einer ökonomischen Stress-Situation kann der Fehler leicht 1,8 % (6.8 % des richtigen VaR) betragen.

Das Ergebnis ist relevant für Risikomanager und Bankenaufseher, denn Banken, die den Ratingimpuls vernachlässigen, halten möglicherweise nicht ausreichend Kapital vor.

Contents

The Impact of Downward Rating Momentum on Credit Portfolio Risk[1]

1 Introduction

Rating transition probabilities play an important role in state-of-the-art credit risk management. Numerous credit portfolio models such as CreditMetrics are based on estimates of rating transition probabilities. Hence, using estimates of these probabilities that are as accurate as possible is crucial for banks, investors in fixed income markets, and—indirectly—for regulatory authorities. A standard specification for rating transition probabilities is the first-order, time-homogeneous Markov model, which is based on the assumptions that, first, the probability of migrating from one rating class to another depends on the current rating only, and second, that the probability of changing from one rating class at time t to another class at time $t+n$ does not depend on t.

However, it is well known that rating transition probabilities are not Markovian. First, they are not homogeneous in time (e.g., Lando and Skødeberg, 2002). Second, it is known that the transition probabilities are influenced by several factors, which can—and usually do—lead to non-Markovian transition probabilities. Rating transitions follow the business cycle in that downgrades are more frequent in recessions than in booms (Nickell *et al.,* 2000; Bangia *et al.,* 2002; Krüger *et al.*, 2005). Transition probabilities also depend on the bond's age (Altman and Kao, 1992; Kavvathas, 2000). Third, Altman and Kao (1992), Christensen *et al.* (2004), and Lando and Skødeberg (2002) show that consecutive rating changes in the same direction are more frequent than in the opposite direction.[2] Since the effect is stronger in the case of downgrades, it is called downward momentum.

Although several factors are identified as contradicting the standard Markov model, their impact on credit portfolio risk is analyzed for some of these factors only. Obviously, the impact is crucial to banks, investors in fixed income markets such as pension funds and insurance companies, as well as to regulatory bodies. To our knowledge, only the outcomes of different

[1] Acknowledgement: We thank Albert L. Chun, Klaus Düllmann, Axel Eisenkopf, Ulrich Krüger and participants at the annual meeting of the German Academic Association for Business Research and the annual meeting of the German Finance Association for their helpful comments. All errors and opinions expressed in this paper are, of course, our own. Financial support by the E-Finance Lab Frankfurt is gratefully acknowledged.

[2] However, Mählmann (2006) and Krüger *et al.* (2005) find no evidence of downward momentum in the case of changes of internal ratings and for a purely scoring-based rating system, respectively.

business cycles have been used for Value-at-Risk (VaR) approaches. Bangia *et al*. (2002) estimate separate transition matrices for booms and recessions and find corresponding 99% VaR figures[3] of a representative portfolio to differ by 29.9%. Krüger et al. (2005) apply this approach to a scoring-based rating model and find the 99% VaR to be more than twofold in the recession period.

As the impact of the other factors on portfolio risk has not yet been analyzed, our research question is the following: how does the VaR change if we incorporate the downward momentum of credit ratings into an appropriate portfolio model? We concentrate on the downward momentum because it is, up to now, the best-analyzed influencing factor of rating transition probabilities.

Our approach is a special case of the model of Christensen *et al.* (2004). Using a dataset with S&P ratings covering the period 1996–2005, we first estimate, as a benchmark, a standard Markov time-homogeneous rating transition matrix, called the *insensitive* matrix. We then estimate a further transition matrix that includes the effect of previous downgrades, called the *momentum-sensitive* matrix. This matrix distinguishes between two groups of firms. One group includes firms with a downgrade as the last rating transition. Following Christensen *et al.* (2004), we call these firms *excited*. The second group comprises the remainder of the sample.

To quantify the impact of the rating momentum on credit portfolio losses, we take the perspective of an investor who holds a portfolio with a fixed rating distribution. By assumption, the investor does not take previous downgrades into account. From his perspective, all risk characteristics of the portfolio are fixed and he therefore uses the insensitive transition matrix to quantify the portfolio risk. We assess to what extent the investor could do better if he incorporated the excitement status of each bond and used the momentum-sensitive transition matrix. To put it differently, we quantify the investor's *risk of ignorance* that is realized in spreads between the investor's calculation of the portfolio VaR and the momentum-sensitive VaR that accounts for excited states. Since the *excitement ratios*, i.e. the number of previously downgraded companies divided by all rated companies in a certain rating class, vary significantly over time, we conduct our analysis for each year separately.

We find evidence of the downward momentum and thus confirm previous findings (e.g. Christensen *et al*. 2004) for our dataset and our simplified methodology. We then analyze the

[3] An x% value-at-risk is defined as the quantile of the loss distribution at the significance level of x%.

representative investor's risk of ignorance and find momentum-sensitive VaRs to be substantially higher than the insensitive VaR. Thus, our hypothetical investor underestimates the portfolio VaR. In a base case scenario, we observe that the momentum-sensitive 99.9% VaR is, on average, 0.24% larger than the insensitive VaR. As the representative investor randomly selects excited bonds from a certain year's pool of available bonds, there is substantial variation in the momentum-sensitive VaRs. The difference between their 5th and 95th percentile of a year's sample is between 0.26% (1997) and 0.44% (2004). Moreover, we find vast variation over time, since the average difference between insensitive and momentum-sensitive VaR reached a maximum of 0.5% in 2004 and a minimum of 0.03% in 1998. In a stress test scenario, we combine a relatively risky portfolio with a high asset correlation of 0.4331. We find VaR deviations of more than 1.7%. The result is, for example, relevant for risk managers and regulators, since banks who neglect the downward rating momentum might hold insufficient capital.

Our analysis contributes to the existing literature in two ways. First, we provide an approach of calculating rating transition probabilities that is strictly based on observables. In doing so, we transfer the findings of Christensen *et al.* (2004) to a setup that is both easily applied and accessible to validation. Second, we explicitly point out the economic impact of including the downward rating momentum into VaR calculations. Hence, our work is complementary to the line of literature that analyzes the impact of the business cycle upon credit portfolio risk (e.g., Bangia *et al.*, 2002).

The article is structured as follows. Section 2 describes our data. Section 3 presents the relevant features of momentum-sensitive transition matrices and the corresponding portfolio VaR. It further describes two explanations for the found relationship between the insensitive and the momentum-sensitive VaR. Section 4 provides empirical results. Section 5 concludes.

2 Data description

Our study covers the period 1996−2005. We use changes of S&P ratings, which were taken from Bloomberg. Given the broad range of different ratings for a given obligor, for example, regarding seniority or collateral, we construct a single rating history for the senior unsecured debt of each issuer. Following Christensen et al. (2004), we make use of a mapped rating scale with seven rating classes from AAA to CCC throughout, since the data would be spread too sparsely over a full scale with + and – modifiers. We treat withdrawn ratings as not containing risk-relevant information. Hence, we eliminate companies whose ratings are withdrawn and distribute their transition probabilities among all other rating classes in proportion to their values (Hanson and Schuermann, 2006).

We use an international sample with 11,230 rated companies. The total number of rating observations is 24,048. According to Table 1, we observe 2,448 upgrades and 6,029 downgrades; the remainder consists of initial rating observations or withdrawal information. The dominance of downgrades is consistent with the findings of Blume *et al*. (1998). In our sample, which covers, for example, the Asian/Russian financial crisis 1997/1998 and the economic slowdown in 2001, the ratio of downgrades to upgrades is even more pronounced than in Blume *et al*. (1998).[4]

In addition to the rating history of the ten years, we also use rating information of the period 1990−1995 for conditioning the rating changes of 1996−2005 on start ratings. Since we are particularly interested in the downward rating momentum, we condition all rating changes on whether or not the previous rating change was a downgrade.

Table 2 provides further insights into the development of the *excitement ratio*, i.e. the ratio of rating changes that belong to previously downgraded companies. Two results emerge immediately. First, the excitement ratio increases for worsening rating levels. Whereas the weighted excitement ratio equals 11.2% for the rating class AA, the figure raises to 70.3% for the most risky rating class CCC. Second, we observe a marked time-pattern since the weighted excitement ratio peaked in 2004, where it reached 28.9% and exhibited a minimum of 11.9% in 1998.

We treat the rating categories D (default), SD (selected default), and R (regulated) as default.[5] In addition, we check the accuracy of the ratings based default information with S&P's annual default reports. As a result, we observe 972 defaulted issuers. Of these, 76 issuers defaulted several times. Almost 60% of the sample companies stem from the U.S. The leftover is mainly distributed over Europe (18.53%), Asia (9.83%), and South and Central America (4.24%).

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[4] An additional reason might be that we include non-US domiciled companies in our sample. These companies experienced many downgrades during our observation period.

[5] The 'R' rating indicates that an obligor is under regulatory supervision owing to its financial condition. Using D, SD and R ratings as defaults, we follow the approach used by S&P's in its annual default reports (cf. S&P 2007).

3 Methodology

3.1 Momentum-sensitive rating transition matrices

Rating transition matrices used in practice tend to have a very simple structure. Using the cohort method, these matrices are calculated on an annual basis. The transition probability, following a constant cohort of companies from the beginning of the year t until the end of the year is given by a transition matrix $P(t)$ where the (h, j)th element denotes the probability that a rated company starting in rating class h at date t is in rating class j at date $t+1$: Let $N_{hj}(t)$ denote the number of rating changes from h to j in the interval $(t, t+1]$ and $N_h(t)$ the number of rating observations in rating class h at time t. The maximum likelihood estimator of $P_{hj}(t)$ is given by

$$\hat{P}_{hj}(t) = \frac{N_{hj}(t)}{N_h(t)}. \tag{1}$$

This approach ignores rating changes if there is more than one within a calendar year. It cannot handle censoring properly either (c.f., Lando and Skødeberg, 2002).

To avoid these problems, we use a simplified approach of the hidden-Markov estimates used by Christensen *et al.* (2004). We consider a homogeneous finite-state Markov chain with one day as time interval where state 1 indicates the highest rating category (AAA); the last state denotes default. Yet, to capture the influence of the downward momentum, we split each rating category into two states according to the following definition: *at a given point in time, a company's rating is called* excited *if the last rating change was a downgrade. It is called* non-excited *otherwise, including the cases without any previous rating change. Whether a company is excited or not is called its* excitement status.

We use the labels (AAA', AA', A', BBB', BB', B', CCC') for the non-excited states and tag excited states with asterisks. Since rating class AAA cannot be reached via downgrades—in contrast to state D, which must be preceded by a "lethal" downgrade—there are only six excited states AA*, A*, BBB*, BB*, B*, and CCC*. In total, the state space is

$S := \{\text{AAA', AA', AA*, A', A*, BBB', BBB*, BB', BB*, B', B*, CCC', CCC*, D}\}$. Let us stress that we use the term *state* to describe jointly the rating class and the "excitement" status.

Figure 1 indicates which direct transitions are feasible according to our definition of an excited state. Note that both off-diagonal probabilities within one rating class (such as AA* → AA' and AA' → AA*) are zero. Excited states can only be entered by downgrades, which means that direct transitions like AA' → AA* cannot occur. Nevertheless, it would be possible to imagine *hidden* transitions from excited to non-excited states (like AA* → AA'), as Christensen *et al*. (2004) actually do. As such transitions cannot be observed, they estimate the probabilities of these hidden moves by a maximum-likelihood algorithm, jointly with all other probabilities whose transitions are observable.

By contrast, we place the emphasis on simplicity and reliability: In setting all transition probabilities within one rating class from excited to non-excited states equal to zero, we rely entirely on observations. In other words, we follow the rule "once excited, always excited, until any observable transition", thus giving the term "excited" a rather broad interpretation.

Given any day t of the estimation period 1996–2005, we can directly assign each rated company k a state $X(t,k) \in S$, while using the period 1990–1995 only to decide whether the last rating change—if there is any—was a downgrade.

Following Lando and Skødeberg (2002), we estimate a continuous-time Markov model, thus exploiting the fact that, given the low frequency of rating changes, the hypothetical continuous-time process is well approximated by a process on a daily scale. Let Y_i be the total of days within the estimation period 1996–2005 that any company of our sample was in state i; formally, we set $Y_i := \sum_{t,k} I_{\{X(t,k)=i\}}$. Let, furthermore, N_{ij} for $i \neq j$ be the total number of transitions from state i to j within the estimation period and $N_i := \sum_{j \neq i} N_{i,j}$ their sum over destination states. The maximum-likelihood estimator $\hat{A}$ of the generator is then given by

$$\hat{A} = \begin{pmatrix} -\frac{N_1}{Y_1} & \frac{N_{1,2}}{Y_1} & \cdots & \cdots & \frac{N_{1,14}}{Y_1} \\ \frac{N_{2,1}}{Y_2} & -\frac{N_2}{Y_2} & \cdots & \cdots & \frac{N_{2,14}}{Y_2} \\ \vdots & \vdots & \ddots & \cdots & \vdots \\ \frac{N_{13,1}}{Y_{13}} & \frac{N_{13,2}}{Y_{13}} & \cdots & -\frac{N_{13}}{Y_{13}} & \frac{N_{13,14}}{Y_{13}} \\ 0 & 0 & \cdots & \cdots & 0 \end{pmatrix}.$$

The bottom row is zero because we assume that firms cannot leave the default state. Furthermore, the generator has zero entries in exactly the same fields as Figure 1 has. From the estimated generator, each transition matrix over a horizon of T days is calculated by

$$\hat{P}(T) := \exp\{T\hat{A}\} = \sum_{k=0}^{\infty}(k!)^{-1}T^k\hat{A}^k \tag{2}$$

via numerical iteration. The one-day transition matrix $\hat{P}(1)$ according to (2) has strictly positive entries, except in line 14 and column 12[6]. However, the one-day transition matrix is very close to the generator, except on the diagonal. We refer to $\hat{P}(365)$, i.e. to the transition matrix over one year, as the *momentum-sensitive rating transition matrix*.

3.2 Insensitive rating transition matrices

To measure the portfolio effect of the downward momentum, we need a benchmark model, used by an investor who ignores the momentum. We assume that he estimates an analogous continuous-time Markov model which recognizes the ordinary ratings AAA, AA, A, BBB, BB, B, CCC, and D only. We estimate the 8×8 generator as an analog to $\hat{A}$ and calculate the corresponding one-year transition matrix, calling it the *insensitive rating transition matrix*.

3.3 Calculating the portfolio VaR

We employ a methodology similar to CreditMetrics (Gupton *et al.*, 1997), which generates defaults and rating transitions in a stylized version of Merton's (1974) asset value model. Following Merton, a firm is assumed to default if the value of its assets falls below a critical level that is defined by the value of liabilities. Below, a firm's asset return X_i is modeled through a one-factor model

$$X_i = \sqrt{\rho}Z + \sqrt{1-\rho}\varepsilon_i \tag{3}$$

where Z is the common factor and ε_i the idiosyncratic risk of obligor i. The random variables Z and ε_i are i.i.d. and standard normal. The asset correlation is therefore equal to ρ. In a next step, the company's asset return determines its evolution of credit ratings. A very sharp decrease in the company's asset value makes the company default; a sufficient decrease

[6] According to our model, the state CCC' cannot be entered through migration from existing other rating during the observation period.

yields a downgrade, and a sufficient increase an upgrade. Otherwise, the company remains in the current rating class. Thresholds for the asset return are calculated according to one of the rating transition matrices analyzed (Table 3 or 5). Let p_{kj} be entry (k, j) of one of these transition matrices and def be the index of the last column, which contains default probabilities. Given a company in state k, the default threshold $Z'_{k,def}$ is given as $Z'_{k,def} = \Phi^{-1}\left(p_{k,def}\right)$, where Φ^{-1} denotes the inverse standard normal cumulative density function. The thresholds to non-default states r are determined by

$$Z'_{k,r} = \Phi^{-1}\left(\sum_{i=r}^{def} p_{k,i}\right) \tag{4}$$

with $\Phi^{-1}(1) := +\infty$, leading to $Z'_{k,1} = +\infty$. When a realization of X_i has been drawn, the lowest threshold above X_i is selected from $\left\{Z'_{k,1},\ldots,Z'_{k,def}\right\}$. Its corresponding state defines the company's new, one-year-ahead rating. Having drawn a new non-default rating, we use corporate credit spreads to calculate the net present value of a hypothetical bond of the company. In the case of default, we derive stochastic recovery rates by using a beta distribution.

On the portfolio level, each simulation step consists of drawing all asset returns according to (3), followed by assigning new ratings, drawing the stochastic recovery rates for all defaulted bonds, calculating individual (dollar) changes of present values and aggregating them to a single random change of the portfolio's present value, which we call the portfolio's profit and loss (P/L).

Simply repeating this procedure yields a Monte Carlo approximation of the P/L distribution and its quantiles. We apply this procedure when calculating the expected return. Yet, when determining quantiles in the lower tail of the distribution, we use importance sampling, which is far more efficient in that case.

3.4 Momentum-sensitive VaR

To quantify the portfolio impact of the rating momentum, we take the perspective of an investor who holds a portfolio of 250 bonds with a fixed rating distribution. As a base case, we assume the rating distribution of the average S&P's rating universe in our observation period also to be representative for the investor.

We first investigate a scenario where the investor ignores prior downgrades. From his perspective, all risk characteristics of the portfolio are fixed; he therefore uses insensitive transition probabilities to assess the portfolio risk. But the investor could assess the portfolio risk more precisely by using momentum-sensitive probabilities.

We therefore define the *risk of ignorance* as the difference between the investor's insensitive VaR calculation and the more sophisticated momentum-sensitive VaR, both being calculated for the same confidence level $1-\alpha$. When the VaR difference is positive, the investor *under*-estimates the portfolio risk by using the insensitive VaR.

In a second scenario, we assume that a more sophisticated investor selects only non-excited bonds for his portfolio. In doing so, he does not just improve the risk assessment but also changes the risk. Since the *excitement ratios*, i.e. the number of previously downgraded companies divided by all rated companies in a certain rating class, significantly vary over time, we conduct our analysis for each year separately. Note, however, that both the insensitive and the momentum-sensitive matrix are time-homogeneous or, in other words, they do not change over time.

In each rating class, the investor holds a fixed number of bonds, regardless of the year he is in. The distribution of exposures in the portfolio is also fixed but inhomogeneous. We assume that the investor, who is in a certain year, randomly selects the bonds needed for each rating class from that year's universe of available bonds. As some of these bonds are excited, the number of excited bonds (drawn without replacement) in each rating class is hypergeometrically distributed. The assignment of bonds to the inhomogeneous exposures is also random and independent of the excitement statuses.

In the first scenario, for each draw of the portfolio, and thus of excitement statuses, we calculate the momentum-sensitive VaR of the portfolio and take the difference to the constant insensitive VaR. Repeating the portfolio draw 100 times for each year provides us with an approximate distribution of the difference between insensitive and momentum-sensitive VaR. This distribution is our measure of the risk of ignorance.

In the second scenario, we conduct the same random excitement analysis as before but contrast the momentum-sensitive VaR (with random excitement statuses) with the momentum-sensitive VaR of the portfolio held by the sophisticated investor who has chosen non-excited loans only.

3.5 Insensitive VaR versus mean momentum-sensitive VaR

It is not immediately clear how, in the first scenario, the constant insensitive VaR relates to the distribution of the momentum-sensitive VaR, which is random due to random choices of excited/ non-excited bonds. Is the momentum-sensitive VaR centered on the insensitive VaR or, if not, what is the sign of the bias in terms of mean values?

We identify two forces that act in opposite directions. The first one leads to a decrease of the mean momentum-sensitive VaR compared with the insensitive VaR. Given that, in pure-default asymptotic single-risk-factor models, according to (3), the VaR is concave in the PD, Jensen's inequality makes the mean momentum-sensitive VaR lower than the insensitive VaR, provided that the momentum-sensitive VaR is a mixture of relatively high (excited) and low (unexcited) PDs.[7]

The second force is based on the nonlinear relationship between momentum-sensitive PDs and the insensitive PD. The effect of Jensen's inequality is based on the assumption that the ignorant investor observes an average (over excitement statuses) of *annual* PDs. By contrast, we actually assume that he estimates the eight-state transition matrix on a *daily* basis and transforms it to the annual transition matrix via (2) as well as a sophisticated investor does in his 14-state model. Indeed, the one-day insensitive transition matrix is almost exactly equal to an average of the momentum-sensitive matrix[8], weighted at the share of excited / non-excited companies, but this property becomes totally lost under the expansion to the one-year matrices. To illustrate this, we concentrate on PDs, as defaults are the crucial contribution to the VaR.[9] We calculate $\hat{P}(t)$ for different risk horizons t and compare the momentum-sensitive t-day PD for the initial states BB' and BB* with the insensitive PD for the initial rating BB. Figure 2 shows the evolution of the PDs from a risk horizon of one month up to three years. The daily insensitive PD (i.e., $t=1$) is virtually the same as an average of the momentum-sensitive PDs with weights equal to the share of excited / non-excited BB-rated companies. But the insensitive PD grows at lower speed than the momentum-sensitive PDs and even falls short of the non-excited PD. There is nothing like a "monotonicity" in these transition prob-

[7] This is easy to show in a pure-default Vasicek setup. The omitted proof is available upon request.

[8] The relationship is exact for the generators; off the diagonal, the one-day matrices and the generators almost coincide.

[9] If the LGD in our model is set equal to zero, the portfolio VaR collapses to about one-fifth of the VaR with a mean LGD of 52%.

abilities. Thus, the insensitive VaR can be lower than the momentum-sensitive VaRs on average, given that the insensitive PD is even lower than both the momentum-sensitive ones.[10]

4 Empirical results

4.1 Momentum-sensitive rating transition matrices for the period 1996–2005

In the first step, we derive insensitive rating transition probabilities as a benchmark for the momentum-sensitive case. Table 3 shows that annual default rates increase with the rating classes from AAA to CCC, as should be expected. As the continuous-time model allows for multiple intra-year transitions, one-year default rates are greater than zero even in the safest rating class AAA, although no AAA-rated company in the dataset defaulted directly (cf. Table 1).

In the next step, we derive momentum-sensitive rating transition matrices to check whether there is downward momentum in our data set. First, this is done in order to replicate the results of Christensen *et al.* (2004), i.e. to ensure that we are in the same empirical context. Second, we will use the momentum-sensitive rating transition matrices for credit portfolio risk calculations. Table 4 provides daily rating transition probabilities according to Figure 1 that are directly based on the observed non-excited and excited rating changes. Empty fields have zero probability by construction: apart from persistence, excited rating states can be entered by downgrades only and non-excited ratings by upgrades only. As we are particularly interested in the probabilities of default, we apply z-tests to their relationship between excited and unexcited states. The excited states have significantly higher default probabilities than the non-excited ones for the rating classes BBB, BB, B, and CCC.

Based on the daily rating transition probabilities, we derive the annual rating transition matrix $\hat{P}(365)$, which is shown in Table 5. We find that the probabilities of downgrades and defaults are higher for issuers who have been previously downgraded, except for the highest starting rating classes AA'/AA*[11]. For example, the default rate equals 47.2% in the excited

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[10] However, we do not have a systematic relationship as there are also two cases where the insensitive PD grows faster with t than the momentum-sensitive PDs.

[11] This counterintuitive finding results from the small number of rating changes from AA*.

rating class CCC*, compared with only 19.9% in the non-excited class CCC'.[12] The insensitive CCC default rate (Table 3) of 40.3% lies between the excited and non-excited values.[13] Furthermore, with the exception of rating class AA* and A*, the rating volatility is markedly higher for the excited rating classes, since their probabilities of staying in (and returning to) the starting rating class is always lower than those of the non-excited rating classes.

4.2 Credit portfolio risk—base case results

In this subsection, we first quantify the investor's risk of ignorance in terms of the difference between the insensitive and the momentum-sensitive VaR. For a base case scenario, we use realistic parameters for the credit portfolio model, which are explained below. Special attention must be paid to asset correlations. As they have a strong impact on the VaR in many credit portfolio models, a large amount of literature has focused on estimating adequate correlation levels (e.g., Lopez 2004). In this paper, we use the results of Zeng and Zhang (2001) who use a dataset of weekly returns of more than 27,000 firms from 40 countries covering the period 1988−1996. We use the results of their best-performing model, the Global Correlation Model (Version 2). For our base case, we use the mean asset correlation of 0.1998 for Zeng and Zhang's sub-sample of firms with the fewest missing weekly returns.[14] The other parameters are chosen as follows. We take the average of our sample's yearly rating distributions as a representative rating allotment in the credit rating business. We use beta distributed LGDs with mean 0.5235 and standard deviation 0.2671 representing the empirical loss characteristics of senior unsecured bonds (Altman and Kishore, 1996). The bonds have a uniform maturity of four years. We use moderately heterogeneous bond sizes which range between €50 and €100 within each rating class.[15]

Below, we present differences in the VaR between the insensitive and the momentum-sensitive view for every year from 1996 to 2005. Throughout, we present differences in VaR levels. Negative VaR differences signify a momentum-sensitive VaR lower than the insensitive VaR. Based on the 100 draws per year of the bonds' excitement statuses and subsequent

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[12] As a robustness check, we also duplicate the hidden-Markov estimation of Christensen *et al*. (2004) for our dataset. We obtain even larger differences in the PDs of the excitement status. We adhere to our approach, however, for the sake of brevity and the practical applicability of the model.

[13] Some researchers, for example, Christensen *et al*. (2004) or Hanson and Schuermann (2006), employ bootstrap approaches to derive confidence intervals around estimates of default frequencies.

[14] Our value is close to a "representative" asset correlation of 20% that is used by Löffler (2003).

[15] Since we report the VaR as a percentage of portfolio volume, the total value of the bonds does not matter.

VaR calculations, Table 6 provides several descriptive statistics of the VaR differences for the years 1996−2005. We concentrate on the 99.9% VaR because it is standard under Basel II (BCBS, 2006) and in many bank internal calculations of economic capital. We observe only positive mean and median VaR differences. According to the t-test for the hypothesis that the mean VaR differences equal zero, all differences are significantly larger than zero.[16] Especially strong positive VaR differences are found in the years 2003−2005, which is a period with a relatively high number of previous downgrades (cf. Table 2). In 2004, the mean VaR difference reaches the maximum of 0.5%. In the years 1996−1999, the VaR differences are relatively low. The smallest mean VaR difference is 0.03% in 1998. The average VaR difference over the whole period from 1996−2005 equals 0.24%.

As the year in which the investor selects the portfolio has no impact on the insensitive VaR but well on the momentum-sensitive VaR, the year can be seen as a risk factor of the misperception, just as the portfolio draws. To obtain a general view on the total risk of ignorance, we aggregate the portfolio draws from all years and find substantial variation in this common sample of VaR misperceptions: the standard deviation equals 0.19%; focusing on severe deviations, there is a 5% probability that the momentum-sensitive VaR is underestimated by 0.59%, which is a relative error of −8.1% or worse. In contrast, there is only a 8.1% probability that the momentum-sensitive VaR is overestimated.

Besides the risk of ignorance, we wish to address the perspective of a more sophisticated investor. This investor exploits the downward momentum in that he selects a purely non-excited portfolio. Compared with the portfolio with random excitement, the sophisticated investor experiences a 99.9% VaR that is, on average, 0.66% lower than the mean momentum-sensitive VaR of Table 6. The maximum VaR difference amounts to 0.91% in 2003. Although the ‘non-excited rule’ might seem somewhat unrealistic, this line of thought nevertheless demonstrates the potential economic impact of the downward rating momentum.[17]

Another important question is whether it is advantageous to use the 99.9% VaR or whether we should concentrate on the unexpected loss. To address this issue, we analyze the differences between the expected losses of the momentum-sensitive loss distributions and the single expected loss of the insensitive setup. On average over our observation period, the mean dif-

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[16] Results remain qualitatively unchanged if we apply the non-parametric Wilcoxon signed-ranks test for differences in the median.

[17] We assume that excited and non-excited bonds are equally priced. If that assumption does not hold, the VaR differences should be minor.

ference between the insensitive and the momentum-sensitive expected loss amounts to only 0.03%. However, the standard deviation of the momentum-sensitive expected losses over the full observation period is almost one-half the standard deviation of the momentum-sensitive VaRs. Thus, investors and banks can be mistaken about the expected loss as well and, consequently, about appropriate write-offs. Given that expected loss and VaR are highly correlated in our simulation of excitement statuses, looking at variations of the unexpected loss would underestimate the size of misperceptions. Instead, by relying on the 99.9% VaR throughout, we include possible miscalculations of both the expected and the unexpected loss.

To summarize the results of the base case scenario, the momentum-sensitive VaR in our observation period is, on average, higher than the insensitive VaR. Years with a relatively high excitement ratio particularly bear the risk of underestimating the VaR.

4.3 Explanations for the base case results

In Section 3.5 we identify two potential drivers of the difference between momentum-sensitive VaR and insensitive VaR, namely the concavity of VaR (negative impact) in the PD and the nonlinear relationship between momentum-sensitive PDs and insensitive PDs (positive impact). Since we have provided evidence in the previous section that the VaR difference is indeed positive, i.e. that the momentum-sensitive VaR is, on average, higher than the insensitive VaR, our second force seems to dominate the first one. In this section, we try to disentangle the two potential effects empirically .

The effect of the concave relationship between VaR and PD can easily be analyzed by changing the insensitive rating transition probabilities. Instead of relying on the annualization of daily transition probabilities that are thus influenced by the nonlinear relationship between momentum-sensitive PDs and the insensitive PD, we replace the insensitive matrix by weighted averages of *one-year* momentum-sensitive transition probabilities: the momentum-sensitive rating transition probabilities of Table 5 are weighted by the average excitement ratio (see Table 2) per rating class over the whole observation period. The momentum-sensitive VaR does not differ from the base case results. On average, the mean VaR difference is negative, unlike in the base case. The average difference between the momentum-sensitive and the weighted insensitive VaR is −0.09%. Assuming that only our two discussed potential reasons drive the VaR differences, we could derive the effect resulting from the nonlinear relationship between momentum-sensitive PDs and the insensitive PD. Since the first effect is negative on average, the second effect is larger than the overall result. On average, the nonlinear relationship between momentum-sensitive PDs and the insensitive PD accounts for 0.33%. Variation over time is rather mild: the VaR differences due to the second effect range between 0.29% and 0.35%.

4.4 Sensitivity analysis

In this section we analyze variations of the base case's input parameters. This will serve mainly as a robustness check. We vary the asset correlation, the risk characteristics (i.e. the rating distribution), the bonds' seniority (i.e. the LGD level), the portfolio size, the maturity, and the distribution of exposure sizes. Aggregate results are shown in Table 7.

First, we alter the asset correlation on two sides of the 0.1998 from the base case scenario. We employ relative extreme asset correlations of 0.0824 and 0.4331, which are the 5th and 95th percentile of the estimates of Zeng and Zhang's (2001) Global Correlation Model (Version 2). The range comprehends all typically observed asset correlations (see for instance, Lopez, 2004). In the case of the lower asset correlation, we observe a lower average VaR difference of 0.12% compared with 0.24% in the base case scenario. The higher asset correlation yields a higher mean VaR difference of 0.53%. The span between the minimum 5th and the maximum 95th percentile of VaR differences is also much larger than in the base case. Thus, we find that lower asset correlations reduce the effect of the downward rating momentum whereas higher correlations reinforce it.

Second, we vary the rating distribution of the portfolio. We construct a low-risk portfolio with a mean rating of A and a junk portfolio with an average rating of approximately BB. We thus follow Jacobson et al. (2006) in assessing the impact of differing rating distributions on our results. For the low-risk portfolio, the average VaR difference over the whole observation period decreases to 0.2% (see Table 7). With regard to the junk portfolio, the mean VaR difference increases to 0.36%. In addition, the average standard deviation over the whole observation period is almost threefold compared with the low risk portfolio. Thus, junk portfolios imply much more volatile momentum-sensitive VaR estimates.

Third, we alter the LGD distribution to capture the effect of different bond types on their risk. Results are again summarized in Table 7. Carey (2000) demonstrates that differences in LGDs have a huge impact on required capital. Thus, instead of using LGDs of senior unsecured bonds, we use LGDs that have the loss characteristics of senior secured and subordinated bonds, respectively. Using the first and second moments from Altman and Kishore (1996), the beta distributed LGDs for senior secured (subordinated) bonds have a mean of 0.4211

(0.6866) and a standard deviation of 0.2299 (0.2242). In the case of senior secured bonds the mean VaR difference of 0.18% is somewhat lower than in the base case scenario. Subordinated bonds exhibit an average VaR difference of 0.32%. Thus, the riskier the portfolio is—be it due to the rating distribution or the LGD level—the higher are the differences, on average, between the insensitive and the momentum-sensitive VaR.

Jacobson *et al.* (2006) identify the portfolio size as a vital parameter in credit portfolio analysis. They show that portfolio VaRs decrease for increasing portfolio sizes. Thus, as a fourth robustness check, we alter the number of bonds in the portfolio to 100 and 500, while maintaining the rating distribution. The average VaR difference equals 0.21% for the smaller portfolio and is thus slightly smaller than in the base case (see Table 7). However, the variation over time is larger since the minimum 5th and the maximum 95th percentile of the VaR difference span more than 1.1%, as opposed to 0.79% in the base case. For the large portfolio, we observe an average VaR difference of 0.25%. The variation over time is very mild. Furthermore, the momentum-sensitive VaRs are much more volatile for the smaller portfolio since the average standard deviation of the VaR differences over time is more than twice the figure of the large portfolio. Hence, we observe a diversification effect that corresponds to Jacobsen *et al.* (2006).

To obtain even more realistic results, we now alter two closely related parameters simultaneously, namely the rating distribution and the bond type. This is designed to capture the fact that riskier firms exhibit higher LGDs on average. We restrict this analysis to two sensible cases. First, Panel I of Table 8 provides the VaR differences for a low-risk rating distribution with an average rating of approximately A and LGDs that correspond to secured bonds. We find a mean VaR difference of 0.17% and low variation over time. Second, Panel II shows our findings for a junk rating distribution with an average rating of approximately BB and LGDs that correspond to subordinated bonds. The mean VaR difference over the full observation period increases to 0.46% and represents almost twice the mean difference of our base case. Variation over time is also rather severe with a maximum (minimum) mean VaR difference of 0.97% in 2003 (0.14% in 1999).

We also combine the risky bond portfolio of Panel II and the high asset correlation of 0.4331 to a stress-test-like scenario. In this case, the mean VaR difference jumps to almost 1%, while its 5th and 95th percentile equal 0.31% and 1.86%. The largest mean VaR deviation of one year occurs in 2003 and reaches more than 1.7%. Thus, this stress test reveals that the economic impact of the downward momentum could be very substantial for junk portfolios that show high LGDs. In a stress test scenario, the VaR differences might even reach dramatic levels in years with high ratios of downgrades. In all cases, the mean VaR differences are positive like in the base case.

Apart from the aforementioned variations, we also alter the maturity to two and six years and the distribution of exposures (homogeneous and very heterogeneous). Neither of these further variations causes substantial variations in the base case results.

Finally, it may be asked whether our assumption of homogeneous credit spreads (i.e. their independence of the excitement status) has an impact on our results. Our approach seems feasible since the VaR is driven mainly by defaults: if the LGD in our model is set to zero, the portfolio VaR difference collapses to about one-tenth of the VaR difference in the base case.

5 Conclusion

We present an approach to the calculation of portfolio VaR that extends the standard Markov model of rating transition probabilities. Using a dataset of S&P ratings for the period 1996–2005, we condition the rating transition probabilities on previous downgrades in order to quantify the effect of the downward rating momentum on portfolio risk.

On average over the observation period, investors who account for the downward momentum perceive higher VaRs compared with investors who do not. In a realistic base case scenario, the average difference between the momentum-sensitive and the insensitive 99.9% VaR equals 0.24%. Thus, investors who ignore the downward momentum underestimate the portfolio VaR by 3.5% of the correct value, on average. We find substantial variation over time since the maximum (minimum) mean VaR difference reaches 0.5% in 2004 (0.03% in 1998). When aggregating the draws from all years, the standard deviation of the VaR difference equals 0.2%. The 95th percentile equals 0.6%, hence there is a 5% probability that the investor makes a relative error of –8.1% or worse. In stress test scenarios, the VaR deviation can easily increase to more than 1.8%. This is a relative error of –6.8%. Several variations of the input parameters suggest that the result is robust.

In our observation period, the momentum-sensitive VaR is higher than the insensitive VaR in more than 90% of the observations. Years with a relatively high excitement ratio, in particular, bear the risk of severely underestimating the VaR. The result is relevant from a risk management and regulatory perspective as it indicates, for example, that banks which neglect the downward rating momentum effect might hold insufficient capital. Our approach can easily be implemented and provides means of calculating a more risk-adequate VaR.

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Table 1

Distribution of rating changes

From \ To	AAA	AA	A	BBB	BB	B	CCC	Default
AAA		189	12	1	0	0	0	0
AA	45		679	36	1	1	0	0
A	25	329		1001	35	10	1	0
BBB	6	39	619		879	77	8	13
BB	2	10	29	503		1067	72	21
B	1	7	27	27	551		988	152
CCC	0	0	3	4	12	209		786

The table provides S&P's rating distribution for the period 1996−2005. We use Bloomberg as the data source for senior unsecured ratings.

Table 2

Excitement ratio development

Rating	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	Average
AAA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
AA	0.0802	0.0728	0.0714	0.0809	0.0778	0.1007	0.1275	0.1518	0.1449	0.1472	0.1120
A	0.1617	0.1544	0.1306	0.1133	0.1182	0.1529	0.1863	0.2369	0.2578	0.2423	0.1813
BBB	0.1415	0.1301	0.1247	0.1354	0.1515	0.1826	0.2114	0.2495	0.2853	0.2705	0.2000
BB	0.1206	0.0881	0.1064	0.1310	0.1597	0.1934	0.2243	0.2875	0.2731	0.2523	0.2000
B	0.1327	0.1235	0.1326	0.1498	0.1787	0.2106	0.2655	0.3489	0.3353	0.2837	0.2344
CCC	0.6875	0.7143	0.6296	0.7899	0.6712	0.6824	0.7597	0.7280	0.6875	0.6548	0.7025
Average	0.1358	0.1226	0.1190	0.1362	0.1498	0.1821	0.2226	0.2705	0.2786	0.2574	

The table shows the development of excitement ratios in the observation period. Excited ratings are defined such that the rating results from a previous downgrade. The averages are calculated by weighted arithmetic means, i.e. years or rating classes with a large number of rating changes are given a high weight.

Table 3

Annual insensitive transition probabilities of S&P ratings

From \ To	AAA	AA	A	BBB	BB	B	CCC	Default
AAA	0.89255	0.09621	0.01020	0.00099	3.714E–05	1.154E–05	8.163E–07	5.597E–07
AA	0.00507	0.91124	0.07677	0.00640	0.00034	0.00016	1.031E–05	5.800E–06
A	0.00146	0.01873	0.91897	0.05645	0.00342	0.00083	0.00010	5.676E–05
BBB	0.00037	0.00259	0.03504	0.90588	0.04764	0.00668	0.00075	0.00106
BB	0.00019	0.00102	0.00364	0.04472	0.84567	0.09062	0.00893	0.00520
B	0.00011	0.00075	0.00291	0.00418	0.05201	0.83008	0.07105	0.03892
CCC	8.837E–06	6.813E–05	0.00169	0.00237	0.00891	0.09639	0.48750	0.40306
Default	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000

Rating transition probabilities are calculated by using the continuous-time estimator for the period 1996–2005, based on daily transitions. We use Bloomberg as the data source for senior unsecured ratings.

Table 4

Daily momentum-sensitive transition probabilities of S&P ratings

From \ To	AAA	AA’	AA*	A’	A*	BBB’	BBB*	BB’	BB*	B’	B*	CCC’	CCC*	Default
AAA	0.999688	5.27E–10	0.000292	8.73E–11	1.86E–05	1.1E–14	1.55E–06	3.6E–15	1.78E–10	1.29E–15	4.35E–11	0	1.03E–11	3.15E–12
AA’	1.56E–05	0.999737	2.28E–09	7.58E–10	0.000234	3.66E–11	1.33E–05	4.62E–11	3.82E–07	2.89E–14	3.81E–07	0	2.31E–10	4.51E–11
AA*	1.21E–05	5.57E–09	0.999788	1.72E–10	0.000197	4.49E–14	3.05E–06	2.54E–14	7.15E–10	1.17E–14	3.05E–10	0	9.34E–11	6.25E–12
A’	4.78E–06	5.55E–05	6.99E–10	0.99976	6.53E–09	5.8E–10	0.000172	1.77E–10	6.25E–06	8.96E–14	1.46E–06	0	7.15E–10	4.5E–10
A*	1.82E–06	5.63E–05	2.66E–10	9.02E–09	0.999775	4.33E–10	0.000159	3.42E–10	4.56E–06	1.71E–10	2.73E–06	0	9.09E–07	1.33E–09
BBB’	1.07E–06	6.85E–06	1.56E–10	0.000103	8.1E–10	0.999735	8.86E–09	1.26E–09	0.000142	2.01E–10	1.03E–05	0	1.07E–06	1.71E–06
BBB*	8.12E–07	5.68E–06	1.19E–10	0.000113	6.72E–10	1.62E–08	0.999675	2.89E–09	0.000175	4.58E–10	2.36E–05	0	2.44E–06	4.06E–06*
BB’	2.81E–10	2.79E–06	2.74E–14	7.33E–06	3.26E–10	0.000128	6.48E–10	0.999575	9.09E–09	2.89E–09	0.000268	0	1.54E–05	3.86E–06
BB*	2.7E–06	2.71E–06	3.95E–10	1.08E–05	3.41E–10	0.000184	9.5E–10	4.95E–08	0.999344	7.12E–09	0.000404	0	3.79E–05	1.36E–05***
B’	2.43E–11	8.06E–07	2.37E–15	5.64E–06	9.42E–11	8.46E–06	4.9E–10	0.000147	6.18E–10	0.99957	1.97E–08	0	0.000232	3.65E–05
B*	1.3E–06	6.48E–06	1.89E–10	1.69E–05	7.7E–10	7.8E–06	1.49E–09	0.000242	6.06E–10	1E–07	0.999112	0	0.000532	8.09E–05***
CCC’	1.97E–11	4.38E–10	1.92E–15	6.72E–06	3.42E–14	6.72E–06	5.77E–10	2.02E–05	4.97E–10	0.000497	2.74E–09	0.99880	5.79E–08	0.00067
CCC*	1.78E–11	3.69E–10	1.73E–15	5.56E–06	2.89E–14	8.34E–06	4.78E–10	2.5E–05	6.09E–10	0.000375	3.4E–09	0	0.997676	0.00191***
Default	0	0	0	0	0	0	0	0	0	0	0	0	0	1

A daily rating transition probability denotes the probability of a certain rating change within one day. The matrix is calculated by using rating data for the period 1996–2005 within a continuous-time Markov model. We use Bloomberg as the data source for senior unsecured ratings. Transition probabilities of issuers with a downgrade as the last rating change are assigned to the rating classes marked with an asterisk; the others are marked by high comma. Rating states with an asterisk can thus be entered only by downgrades or staying in the class, and “normal” ratings by upgrades or staying only. By assumption, there is no direct transition between, say, AA’ and AA*. Usually, all probabilities are positive since the continuous model allows for multiple intraday transitions. The states D and CCC’ are exceptions because we assume the default state to be absorbing and because the state CCC’ cannot be entered by migration. Off the diagonal, the one-day transition matrix is very close to the generator. In particular, all transition probabilities are very small (<1E-07) where the generator is zero (cf. Figure 1). We employ z-tests for the null hypothesis that the default probability of an unexcited state exceeds the probability of the corresponding excited state. One-sided significance levels are given as ***, **, and *, representing 1%, 5%, and 10%, respectively.

Table 5

Annual momentum-sensitive rating transition probabilities of S&P ratings

From \ To	AAA	AA	A	BBB	BB	B	CCC	Default
AAA	0.89250	0.09700	0.00966	0.00080	2.82E–05	8.03E–06	1.88E–06	1.05E–06
AA’	0.00516	0.90939	0.07823	0.00663	0.00037	0.00019	2.70E–05	1.42E–05
AA*	0.00405	0.92626	0.06658	0.00292	0.00012	4.56E–05	1.23E–05	5.22E–06
A’	0.00164	0.01865	0.91818	0.05676	0.00370	0.00088	0.00010	8.49E–05
A*	0.00066	0.01892	0.92293	0.05268	0.00307	0.00122	0.00033	0.00018
BBB’	0.00041	0.00267	0.03443	0.91024	0.04411	0.00618	0.00091	0.00105
BBB*	0.00033	0.00230	0.03743	0.89127	0.05408	0.01079	0.00162	0.00218
BB’	3.31E–05	0.00108	0.00346	0.04149	0.86089	0.07780	0.00967	0.00558
BB*	0.00087	0.00114	0.00489	0.05725	0.79378	0.11280	0.01725	0.01201
B’	3.62E–06	0.00031	0.00203	0.00398	0.04627	0.86087	0.05263	0.03390
B*	0.00039	0.00205	0.00543	0.00441	0.07069	0.73506	0.11002	0.07194
CCC’	2.48E–06	5.06E–05	0.00211	0.00238	0.00937	0.13597	0.65108	0.19903
CCC*	2.00E–06	3.78E–05	0.00146	0.00234	0.00826	0.08514	0.43087	0.47188
Default	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000

Annual rating transition probabilities are calculated by the continuous-time estimator for the period 1996–2005. We use Bloomberg as the data source for senior unsecured ratings. Transition probabilities of issuers with a previous downgrade are assigned to the rating classes marked with an asterisk; the others are marked by high comma. Columns three to eight exhibit aggregated transition probabilities of excited and non-excited destination states. The aggregation has no impact on the outcome of the portfolio model as credit spreads in our model depend on the current rating only.

Table 6

VaR differences in basis points for a representative bond portfolio ("base case")

Year	Percentile					Mean	Standard deviation	Negative
	5th	25th	50th	75th	95th			
1996	–2.89	5.45	11.29	16.96	25.17	11.02 ***	8.40	0.0800
1997	–0.86	5.53	10.18	14.82	24.96	10.44 ***	7.85	0.0700
1998	–12.19	–3.92	2.86	8.04	18.67	2.53 ***	9.60	0.4200
1999	–4.19	4.61	9.14	17.12	25.69	10.22 ***	9.25	0.1300
2000	–4.41	7.83	13.10	22.03	34.87	14.69 ***	11.35	0.0800
2001	6.40	15.73	22.34	28.13	39.90	22.52 ***	11.02	0.0200
2002	12.35	25.33	34.22	42.67	54.73	34.24 ***	13.48	0.0100
2003	29.84	41.22	50.11	58.84	66.71	49.53 ***	11.97	0.0000
2004	22.42	38.35	47.27	53.25	66.22	45.52 ***	12.82	0.0000
2005	22.06	29.86	38.19	46.03	59.37	39.43 ***	12.38	0.0000
all years	–3.79	8.83	20.57	38.52	59.04	24.01 ***	19.35	0.0810

The table shows descriptive statistics for the differences between the insensitive VaR (using rating transition probabilities of Table 3) and the momentum-sensitive VaR (using rating transition probabilities of Table 5) for a representative portfolio comprising 250 bonds. Results are calculated as differences in VaR levels and are presented in basis points. In the case of the momentum-sensitive VaR we employ 100 simulations for each year with randomly chosen excitement status (the insensitive VaR is calculated only once as it neither depends on the excitement status nor on the year). We use the 99.9% quantile for both VaRs. The insensitive VaR equals 6.66%. Both VaRs are calculated in a simplified CreditMetrics framework with a horizon of one year. We use importance sampling to decrease the number of simulated portfolio returns to 10,000. We employ an asset correlation of 0.1998 (Zeng and Zhang, 2001) and beta distributed LGDs with mean 0.5235 and standard deviation of 0.2671 for senior unsecured bonds (Altman and Kishore, 1996). The bonds have a uniform maturity of 4 years. We use moderately heterogeneous bond sizes ranging from €50 to €100. Columns 2 to 6 display percentiles of the annual VaR differences. Columns 7 and 8 show the mean and the standard deviation of the annual VaR differences. We employ t-tests for the hypothesis that the mean annual VaR difference equals zero. Two-sided significance levels are given as ***, **, and *, representing 1%, 5%, and 10%, respectively. Column 9 provides the annual ratio of negative VaR differences.

Table 7

VaR differences for several deviations from the base case

Type of sensitivity analysis	Minimum of 5th Percentiles	Maximum of 95th Percentiles	Overall Mean	Mean Standard deviation
Low asset correlation	–23.7717	50.9857	12.4167	10.7618
High asset correlation	9.9382	108.5087	52.9943	11.9573
Low–risk bonds	8.1576	36.2771	19.9298	4.1254
Junk bonds	–20.7633	109.1648	36.2572	15.7023
Low LGD	–14.4880	54.9052	18.4553	9.0298
High LGD	–13.7410	87.7838	31.9064	13.5290
Small portfolio	–26.8966	83.2647	20.7440	18.6897
Large portfolio	1.3259	63.1038	24.9487	7.4462

The table shows descriptive statistics for the differences between the insensitive VaR (using transition probabilities of Table 3) and the momentum-sensitive VaR (probabilities of Table 5) for several sensitivity analyses. Results are calculated as differences in VaR levels and are presented in basis points. In the case of the momentum-sensitive VaR we employ 100 simulations for each year with randomly chosen excitement status (the insensitive VaR is calculated only once as it neither depends on the excitement status nor on the year). We use the 99.9% quantile for both VaRs. They are calculated in a simplified CreditMetrics framework with a horizon of one year. We use importance sampling to decrease the number of simulated portfolio returns to 10,000. If not otherwise stated we used the parameters of the base case (Table 6). In row 1 (row 2) we employ a low (high) asset correlation of 0.0824 (0.4331) according to the 5th (95th) percentile for the estimation of the asset correlation in Zeng and Zhang (2001). In row 3 (row 4) we utilize an average rating that equals approximately A (BB) for the low-risk (junk) bond portfolio. In row 5 (row 6) we employ beta distributed LGDs with mean 0.4211 (0.6866) and standard deviation of 0.2299 (0.2242) to represent low-LGD senior secured (high-LGD subordinated) bonds according to Altman and Kishore (1996). Row 7 (row 8) presents results for a small (large) portfolio that comprises 100 (500) bonds. Column 2 (column 3) displays the minimum of 5th percentiles of the VaR differences (maximum of 95th percentiles) over the observation period. Column 3 (column 4) shows the mean VaR difference (mean standard deviation) over the whole observation period.

Table 8

VaR differences for bond portfolios with altering debt types and rating distributions

Year	Percentile 5th	25th	50th	75th	95th	Mean	Standard deviation	Negative
Panel I: Low LGD & low-risk rating distribution (insensitive VaR: 0.0165)								
1996	9.4059	11.3060	13.8862	15.6865	17.8206	13.6349 ***	2.9719	0.00
1997	7.8891	10.3294	12.0525	14.0125	16.3521	12.1579 ***	2.7191	0.00
1998	7.8001	11.6741	12.7924	14.9163	16.8141	12.9355 ***	2.6997	0.00
1999	8.5401	11.2690	13.2573	15.3794	19.8315	13.4431 ***	3.3358	0.00
2000	9.3239	12.5392	14.7177	16.9868	20.3889	14.8185 ***	3.3756	0.00
2001	10.4389	15.2437	17.1431	20.2420	23.7587	17.6243 ***	3.9618	0.00
2002	13.4949	16.4686	18.1508	21.1581	23.6809	18.6213 ***	3.1984	0.00
2003	15.6248	19.1623	21.8023	25.2639	28.6048	22.2086 ***	4.2447	0.00
2004	18.0066	21.0298	23.0165	25.6346	29.3536	23.3309 ***	3.6522	0.00
2005	16.0389	20.2624	22.2635	24.4412	27.6869	22.2056 ***	3.5034	0.00
Panel II: High LGD & junk rating distribution (insensitive VaR: 0.1654)								
1996	12.6034	26.4812	33.7805	44.0911	55.2171	34.5892 ***	13.3159	0.00
1997	2.4836	14.7858	25.5931	32.3686	44.3822	24.4450 ***	12.8337	0.03
1998	8.5059	22.6988	29.8638	39.9624	53.7854	30.9779 ***	13.5662	0.01
1999	–16.2866	1.4972	14.2618	27.2429	42.1138	14.1785 ***	19.1613	0.24
2000	–16.3219	1.0299	18.2165	27.0809	53.6869	15.8391 ***	21.7144	0.24
2001	–7.7723	20.4052	32.4031	47.5204	67.0607	32.8547 ***	22.8018	0.09
2002	29.9019	48.5672	62.6738	76.2332	113.2917	64.1685 ***	23.7542	0.01
2003	63.9026	80.7147	98.3481	111.3912	130.5881	96.7677 ***	21.5990	0.00
2004	46.1707	70.2636	84.8541	101.0425	118.8673	83.8329 ***	22.9814	0.00
2005	31.5647	44.7393	64.4865	77.2577	98.0243	63.1936 ***	21.9667	0.00

The table shows descriptive statistics for the differences between the insensitive VaR (using rating transition probabilities of Table 3) and the momentum-sensitive VaR (probabilities of Table 5) for a representative portfolio with 250 bonds. Results are calculated as differences in VaR levels and are presented in basis points. In this case, we vary the rating distribution and the debt type simultaneously. Panel I implies a low-risk rating distribution with an average rating of approximately A and LGDs of secured bonds. Panel II implies a junk rating distribution with an average rating of BB and LGDs of subordinated bonds. In the case of the momentum-sensitive VaR we employ 100 simulations for each year with randomly chosen excitement status (the insensitive VaR is calculated only once as it neither depends on the excitement status nor on the year). We use the 99.9% quantile for both VaRs. Both VaRs are calculated in a simplified CreditMetrics framework with a horizon of one year, using importance sampling to decrease the number of simulated portfolio returns to 10,000. We employ an asset correlation of 0.1998 (Zeng and Zhang, 2001). We use beta distributed LGDs with mean 0.4211 (0.6866) and standard deviation of 0.2299 (0.2242) for senior secured (subordinated) bonds for Panel I (Panel II) according to Altman and Kishore (1996). The bonds have a uniform maturity of four years. We use moderately heterogeneous bond sizes ranging from €50 to €100. Columns 2 to 6 display percentiles of the annual VaR differences. Columns 7 and 8 show the mean and the standard deviation of the annual VaR differences. We use a t-test for the hypothesis that the mean annual VaR differences equal zero. Two-sided significance levels are given as ***, **, and * representing 1%, 5%, and 10% respectively. Column 9 provides the ratio of negative annual VaR differences.

Figure 1

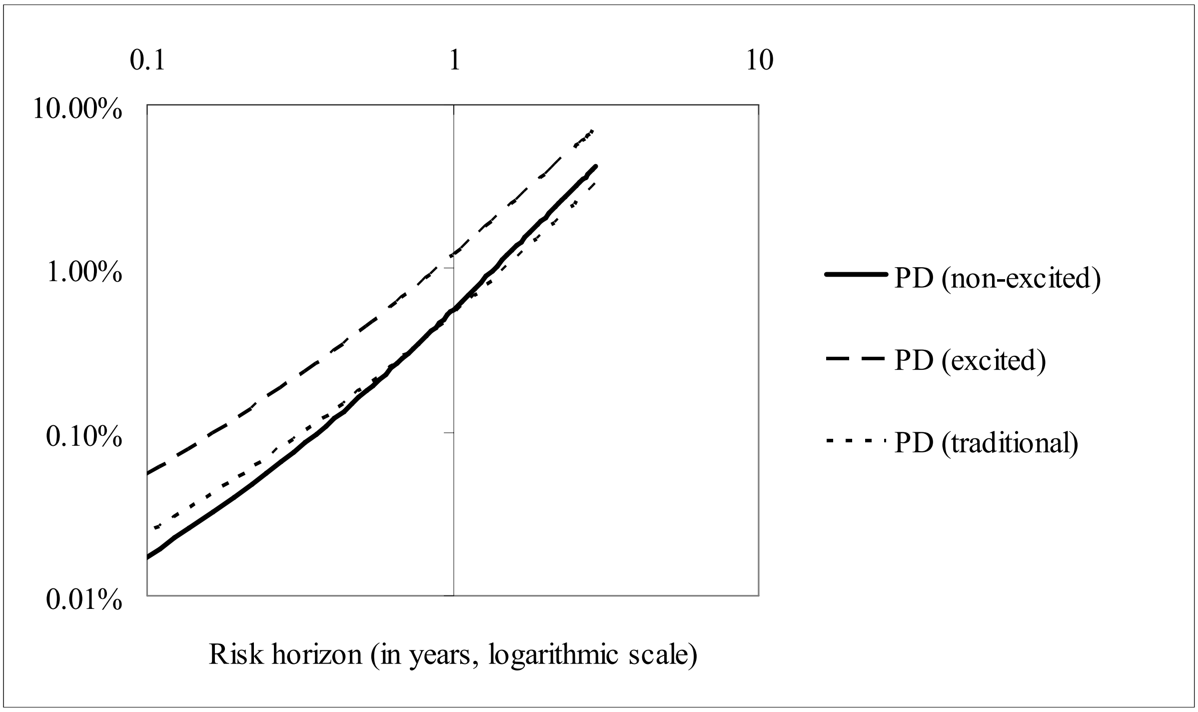
Feasible direct transitions

	From \ To	non-excited							excited						
		AAA	AA’	A’	BBB’	BB’	B’	CCC’	AA*	A*	BBB*	BB*	B*	CCC*	Default
non-excited	AAA	+							+	+	+	+	+	+	+
	AA’	+	+							+	+	+	+	+	+
	A’	+	+	+							+	+	+	+	+
	BBB’	+	+	+	+							+	+	+	+
	BB’	+	+	+	+	+							+	+	+
	B’	+	+	+	+	+	+							+	+
	CCC’	+	+	+	+	+	+	+							+
excited	AA*	+							+	+	+	+	+	+	+
	A*	+	+							+	+	+	+	+	+
	BBB*	+	+	+							+	+	+	+	+
	BB*	+	+	+	+							+	+	+	+
	B*	+	+	+	+	+							+	+	+
	CCC*	+	+	+	+	+	+							+	+
	Default														+

Excited states are tagged with asterisks, non-excited states are marked by high comma. Plus signs denote feasible direct transitions of the continuous-time process. Only in these fields transition intensities may be positive. Direct migration from an excited state to the non-excited state with the same rating is excluded.

Figure 2

Probability of default of a BB rated bond for differing initial excitement statuses



The figure exhibits the probability of default (PD) of a BB rated bond for differing risk horizons. The three bond types exhibit differing excitement statuses at the beginning. Both scales are logarithmic.

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