Rating migration matrices: empirical evidence in Indonesia

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1. Introduction

Credit risk remains the dominant problem confronting banks. Nevertheless, banks need to identify, monitor and control credit risk as well as ensure capital adequacy to anticipate the risk (Basel Committee on Banking Supervision (1999)). Basel II confirmed that financial institutions must have the ability to analyse credit models and internal ratings to ensure the model is calibrated to measure credit risk consistently and meaningfully. Furthermore, credit risk is the main risk faced by financial institutions. Van Deventer and Imai (2003) specifically mentioned that credit risk is the major reason for bank default.

BIS (2005) also confirmed that the main reason for bank failure is low credit quality and poor credit risk evaluation. Poor credit risk evaluation tends to neglect the use of capital requirements to expedite a precise evaluation and tight control of credit risk exposure to a bank.

There are several difficulties in determining credit risk solutions that cover a number of companies. First, credit risk has different types and sizes. Second, the different types of credit risk are generally managed centrally, and are closely monitored. The source of credit risk also varies widely; from corporate or sovereign bonds, credit derivatives, over-the-counter derivatives (such as interest rate swaps), commercial lending, retail mortgages and credit cards. Third, banks tend to manage their credit risk separately from market risk.

In measuring credit risk, Kamakura Risk Information Services (KRIS (2004)) applied three quantitative approaches to model default probabilities, namely: Jarrow Chava model, Merton structural model and Jarrow Merton hybrid model. The three approaches incorporate information regarding a company's equity market prices and interest rates, so that prevailing market expectations can be accommodated in the default probability estimates. Van Deventer and Wang (2003) use this model by estimating default probability explicitly using logistical regression with a historic default database.

In addition to default probability estimates, credit risk analysis can also be performed using risk migration analysis (migration probability of the bond rating). The bond rating is an important indicator to evaluate a company's credit quality, as well as their default probability. A change in a company's rating reflects the credit quality of that company, either improved (upgrade) or deteriorating (downgrade). Analysis of the rating transition, including default, is

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useful in the credit risk model to measure future credit loss. Thus, the matrix containing rating transition probability (transition matrix) plays an important role in credit risk modelling.

Theoretically, the transition matrix can be estimated for the desired transition horizon. However, the matrix commonly used is an annual or five-yearly transition matrix. Specifically, a transition matrix illustrates the default risk and high migration volatility of a low quality portfolio. The default likelihood increases exponentially with a decline in grade. All transition matrices exhibit the same characteristic; they all have high probabilities in a diagonal matrix; the obligor tends to maintain its current rating. The second largest probability is around the diagonal. Meanwhile, the farther from the diagonal, the lower the rating transition (Violi (2004)). A study by Kryzanowski and Menard (2001) shows that the probability of a bond remaining at its initial rating reduces as the time horizon analysed becomes longer.

The discussion on credit modelling not only focuses on the probability of default, but also analyses what is happening to credit that is close to default (McNulty and Levin (2000)). For that reason, researchers began to focus on the probability of credit rating transition from one level to another. One of the representative ways of presenting such information is through a transition matrix.

2. The objective of the research

This research aims to estimate a credit rating transition matrix, specifically used to identify:

- Rating migration at a certain period;
- The heterogeneity of rating migration; and
- The volatility level of rating migration.

3. Literature study

Transition matrix rating

Credit migration, or a transition matrix, indicates changes in the quality of settled credit at a particular company. Transition matrices are the main input in various applications of risk management. One example, in the New Basel Accord (BIS (2001)), capital requirement is based on the rating migration. In 1999, the Basel Committee on Banking Supervision (BCBS) confirmed the use of transition matrices and has since advocated their use as a basis to fulfil the securitisation framework.

Credit rating is a process where any credit rating observation can form one of several state ratings. In this research, it is assumed that the credit rating process follows the Markov chain process. This means that the probability placed on one state can only be determined by knowing the state from its previous observation. The assumption of Markov chain in the credit rating process implies that the credit transition is more time invariant or time homogenous, where the transition probability remains the same towards time and constant during the predetermined horizon.

If one Markov chain has state space S = {1,2,…..k}, the probability of the credit rating process in state j for one observation after being in state i in a previous observation, is denoted by P_{ij}. This P_{ij} is known as the transition probability from state i to state j. A matrix with a transition probability from state i to state j is known as the transition matrix of the Markov chain (Anton and Roses (1987)). Subsequently, the transition matrix is denoted with P. The general format of the one step transition probability matrix is as follows:

$$P = \begin{pmatrix} p_{11} & p_{12} & p_{13} & \cdots & p_{1k} \\ p_{21} & p_{22} & p_{23} & \cdots & p_{2k} \\ \vdots & & & & \vdots \\ p_{j-1,1} & p_{j-1,2} & p_{j-1,3} & \cdots & p_{j-1,k} \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix} \tag{3.1}$$

At equilibrium (3.1) above, P_{ij} verifies the transition probability from state i at time t to state j at time t+1. In addition, the Markov chain transition matrix above has the characteristic that all entries on one line equal 1. Mathematically, that characteristic can be written as follows:

$$p_{i1} + p_{i2} + ... + p_{ik} = 1 \tag{3.2}$$

The state vector X (t) for one Markov chain observation with state space S = {1,2,…..k} is defined as the vector of column x where the i component, namely xi, is the probability of state i at time t. The column vector can be formulated as:

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \end{bmatrix} \tag{3.3}$$

According to theorem by Anton and Rorres (1987), if P is the Markov chain transition matrix and x(n) is the state vector at observation n, it makes:

$$\mathbf{x}^{(n+1)} = P\mathbf{x}^{(n)} \tag{3.4}$$

From 3.4, it is known that:

$$\mathbf{x}^{(n)} = P\mathbf{x}^{(n-1)} = P^2\mathbf{x}^{(n-2)} = P^n\mathbf{x}^{(0)} \tag{3.5}$$

In other words, Equation 3.5 verifies that the previous state vector x(0) and transition matrix P reveal the value of state vector x(n).

4. Specification of the transition matrix approach used

In this study, a transition matrix is constructed for both discrete and continuous timescales. Based on the discrete approach, changes in the obligor rating (credit score) are only monitored after a certain period of time (fixed), such as six months, nine months, one year or other specific periods. Meanwhile, based on the continuous approach, any change in rating can be monitored at any time, even minute-by-minute (Ahmed et al (2004)).

Building a transition matrix using the discrete approach follows Jafry and Schuermann (2004). Meanwhile, the transition matrix based on the continuous approach was adapted from Lando and Skødeberg (2002).

Transition matrix, discrete timescale: cohort method (frequentist)

One method to calculate changes in probability from the data estimated using a discrete timescale is the cohort method. The cohort method has been widely used as it applies simple calculations, although sometimes the results are less efficient.

Transition matrix, continuous timescale:

Constructing a transition matrix using a continuous timescale approach has fascinated many modellers in recent years. Ahmed at al mentioned two key elements when applying this approach:

1. To facilitate the transition probability estimation where the transition to a certain rating rarely occurs, for example an indirect default (default through a sequential downgrade)
2. To facilitate the construction of a transition matrix for all lengths of time (for example the 73-day transition matrix)

Continuous method with the assumption of time homogeneity

Using this approach, we get a K-state Markov chain where state 1 is the highest state and state K is default. The transition probabilities for a certain period are calculated in matrix P(t) Kx where ij is the migration probability from state i to state j during period t. The generator matrix with KxK dimension is Λ with non-negative, off-diagonal entries and the number of lines equal to zero (Israel et al, 2001), where (Lando and Skødeberg (2002)):

$$P(t) = \exp(\Lambda t),\ t \geq 0 \tag{3.6}$$

Matrix Λt is matrix Λ multiplied by t for each entry and the exponential function denotes the exponential matrix. The entry for matrix Λ is:

$\lambda ij \geq 0$, for $i \neq j$

$$\lambda_{ii} = -\sum_{j \neq i} \lambda_{ij} \tag{3.7}$$

This entry explains the probabilistic behaviour of holding time in state i as it is exponentially distributed with parameter λ_i, where $\lambda_i = -\lambda_{ii}$ and the probability of shifting from state i to j is λ_{ij}/λ_i.

The transition probability for each time horizon is the function of the generator. Thus, we can obtain the maximum likelihood estimator from the transition probability matrix using the estimation from the generator. This is subsequently applied to the exponential matrix for the maximum likelihood estimation of that generator.

Based on the assumption of time homogeneity, the element from the matrix generator is calculated using the maximum likelihood estimator as performed by Kuchler and Sorensen (1997):

$$\hat{\lambda}_{ij} = \frac{N_{ij}(T)}{\int_0^T Y_i(s)\,ds} \quad \text{for } i \neq j \tag{3.8}$$

Where:

$N_{ij}(T)$: number of transitions from state rating i to state rating j in the period.

$Y_i(s)$: number of companies with state rating i during s.

In other words, the denominator from Equation 3.8 shows the number of “firm-years” of all companies included in the sample that were initially state i. Thus, the state of each company for each period is also counted in the denominator.

The continuous method with the assumption of time non-homogeneity:

According to a study carried out by Lando and Skødeberg (2002), one of the means to calculate a transition probability matrix from continuous data, assuming non-homogeneity, is by applying the Aalen-Johansen estimator. Based on Jafry and Schuermann (2003), the Aalen-Johansen estimator, or non-parametric product limit, obtained is consistent. The construction of transition matrices using this method follows the cohort method over a very brief period, such as on a daily basis (Landschoot (2005)).

In estimating the transition matrix using a continuous timescale and assuming non-homogeneity, $P(s,t)$ is the transition probability matrix for period [s,t]. Element ij from the matrix notes the Markov probability process, beginning with the transition from state i at time s to state j at time t. Then, if several m transitions are identified during the period [s,t], $P(s,t)$ can be estimated by applying the Aalen-Johansen estimator (Jafry and Schuermann (2003)).

$$\hat{P}(s,t) = \prod_{i=1}^{m} (I + \Delta\hat{A}(T_i)) \tag{3.9}$$

Evaluating rating quality

To intensify the analysis results, several indicators must be observed. One of the most important indicators in evaluating the quality trend of corporate ratings is rating activity. According to Carty and Fons (1993), rating activity can be calculated from the sum of rating shifts, both the upgrades and the downgrades, divided by several issuers operating at the beginning of the year. Another important indicator is rating drift. Rating drift is the dependency on previous ratings and is identified as non-Markovian behaviour (Lando and Skødeberg (2002)). Rating drift is calculated by the total number of upgrades subtracted by the number of downgrades and divided by the number of issuers operating at the beginning of the year. Based on the sample given by Carty and Fons (1993), a rating change from BBB to A represents one rating, whereas from BBB to AA is a change of two ratings.

The discrete hazard model

A credit risk model used to analyse credit risk is known as the hazard rate model. The hazard rate model is a method to measure bankruptcy by including default intensity. The model is widely used in operational measurements. One of the applications of this model is for pricing, bankruptcy and estimating the probability of company default. There are two types of hazard models, discrete hazard rate and continuous hazard rate. The difference between the two models is in the survival function applied. This research paper focuses on discrete hazard. The discrete hazard model is an appropriate model to analyse data consisting of binary observations, time-series and cross-sectional data, as in cases of bankruptcy. The hazard rate is defined in economic studies as the transitional risk of different states. In financial literature, the hazard rate indicates credit default risk.

5. Data sources

The data used originates from PT Pemeringkat Efek Indonesia (Pefindo). Company ratings as well as debt specific ratings published by Pefindo from February 2001 to June 2006 were used to calculate the transition matrices, using both with discrete and continuous methods. However, several bond ratings published by Pefindo also contained the bond rating given by other rating agencies, such as KASNIC.

The rating agency data published during the period consists of a semiannual publication, published every February and August. The publication in February year i is the rating agency data from 31 December year i–1, whereas the publication in August year i is the rating data from 31 June year i. Meanwhile, bond rating data used in the estimation is for the period of 2001–05, published monthly by Pefindo, from July 2003 to June 2006; and a semiannual publication from 2001 to 2002. The data from Pefindo comprises of 115 company ratings and 412 bond ratings from 119 companies. However, not all the data could be included in the estimation due primarily to a lack of available data at the beginning of the estimation period.

6. Analysis results of the transition matrix

6.1 Evaluating rating quality

Figure 6.1 illustrates that the corporate rating quality of the sample, in general, showed improvement. This is indicated by the decline in the percentage of downgraded companies during 2001–04 (from 25% to 3.23%). Nonetheless, in 2005, the percentage of downgraded companies increased to 4%. On the other hand, higher corporate rating quality was evidenced by a rise in the number of upgraded companies, from 10% in 2001 to 14.3% in 2003. However, the percentage declined again in 2004 and 2005. Since 2003, the number of upgraded companies has exceeded the number of downgraded companies. This is a preliminary indication of an improvement in the conditions of the sample companies.

Figure 6.1

Number of upgraded and downgraded companies

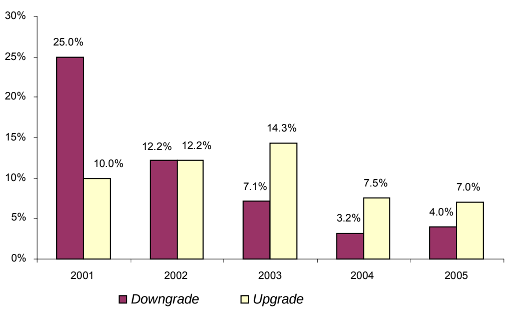
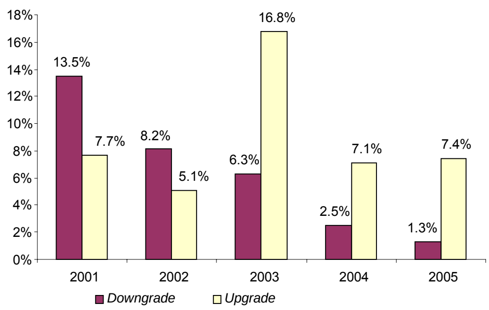


Figure 6.2

Number of upgraded and downgraded sample bonds



Source: Pefindo (processed)

This is further emphasised in Figure 6.2, where the percentage of downgraded bonds has shown a declining trend over the past five years. In 2001, the percentage of downgraded sample bonds was 13.5%, while in 2005 it was only 1.3%. In brief, Figures 6.1 and 6.2 indicate initial improvements in the creditworthiness of sample companies issuing bonds. This was buttressed by the fall in both downgraded companies and bonds, as well as the rise in the percentage of upgrades.

Rating activity and rating drift:

A positive (+) rating drift shows that the number of upgrades has surpassed the downgrades, more specifically indicating an improvement in rating quality. Conversely, a negative (–) rating drift shows that the number of downgrades has surpassed the upgrades, ergo a decline in credit quality. In brief, rating drift indicates whether a rating shows any improvement or decline over a certain period of time.

The rating activity and rating drift of sample companies during 2001–05 is presented in Figure 6.3. It can be seen that there was a regression in letter activity rating of the sample companies from 2001–04. However, in 2005, rating activity increased to 15%.

Even though the percentage of rating activity showed a decline, conversely, the rating drift experienced an escalating trend. This indicates that despite an unsatisfactory activity rating for the sample companies over the past few years, the rating is beginning to show improvement. In 2001 and 2002, the rating drift was negative (–), which means that the number of downgrades exceeded the upgrades. However, the rating drift has declined since 2004 but not as severely as during 2001 and 2002.

Figure 6.3

Letter rating activity and rating drift of a sample companies

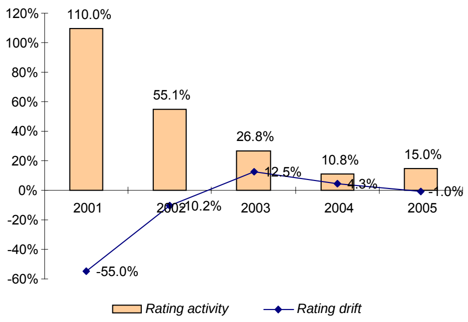
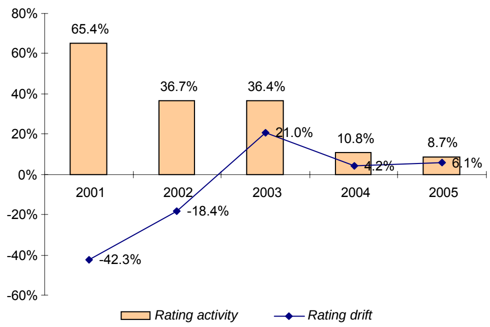


Figure 6.4

Letter rating activity and rating drift of sample bonds



Source: Pefindo, processed

Figure 6.4 shows the letter rating activity and rating drift of sample bonds from 2001–05. The percentage of letter rating activity of sample bonds has declined, from 65.4% in 2001 to 8.7% in 2005.

Despite a decline in rating activity, rating drift improved, which is shown by its escalating trend. This means that even though the percentage of activity rating over the past few years experienced a decline, the rating still showed improvement.

In 2001 and 2002, the rating drift was negative, which means the number of downgrades exceeded the upgrades. However, the rating drift continued to increase reaching 21% in 2003, which indicates that the number of upgrades outperformed the downgrades, as experienced by the rating drift in sample companies.

More concisely, it can be concluded that the percentage of rating activity and sample bonds during 2001–05 declined relatively. Nevertheless, rating activity showed improvements as indicated by the positive rating drift. This is initial evidence of improved creditworthiness for sample bonds over the past few years.

6.2 Analysis of the transition rating matrix

There are two main approaches to estimating a transition matrix: the cohort method and the continuous/discrete method. The continuous method was identified based on time homogenous and time non-homogenous assumptions. In this study, the transition matrix is estimated using the cohort method and continuous method assuming time homogeneity.

In constructing a transition matrix based on a discrete timescale, the cohort method was used derived from Jafry and Schuermann (2004). Meanwhile, the transition matrix based on a continuous timescale approach was adapted from the study by Lando and Skødeberg (2002).

Company rating transition matrix:

Cohort method

The company rating transition matrix was estimated using the cohort method annually, semiannually (2004–05), every three years (2003–05), every four years (2002–05) and five years (2001–05). To summarise, a few salient matrices are presented.

The five-year transition matrix (2001–05):

Based on the cohort method, the total number of transitions during 2002–05 was 19, with one "not rated" transition. The results are presented in Table 1. The estimation results for 2001–05 show no symmetrical relationship between rating stability and rating level. This is indicated by the diagonal value, which does not represent stability waning in line with a deterioration in the rating.

The estimation results also show that rating activity remained concentrated around the diagonal, even though several ratings displayed extreme changes. This implies that in a five-year period, there is the possibility of significant credit migration.

Table 1 shows that there is a 14.29% probability of upgrading an AA rating, but also a 4.76% chance of downgrading. Another rating that experienced an upgrade was BBB with a probability of 44.44%. Furthermore, a BB rating has the same transitional probability as a B rating, namely 66.67%, to a higher rating. The improvement in rating BBB is negated by the 11.11% decline of rating B. In addition, rating CCC also experienced a transitional probability of 100% to a higher rating. However, there is only one observation at the beginning of the period for this rating.

Table 1

Corporate rating transition matrix based on the cohort method

%, 2001–05

	Number of companies at period end	**AAA**	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**D**	**NR**
AAA	1	100	0	0	0	0	0	0	0	0
AA	2	0	50	50	0	0	0	0	0	0
A	21	0	14.29	61.90	4.76	0	0	4.76	14.29	0
BBB	9	0	0	44.44	44.44	0	11.11	0	0	0
BB	3	0	0	0	66.67	0	0	0	0	33.33
B	3	0	33.33	33.33	0	0	33.33	0	0	0
CCC	1	0	0	100	0	0	0	0	0	0
D	0	0	0	0	0	0	0	0	0	0
NR	0	0	0	0	0	0	0	0	0	0
Total	**40**									

From 2001–05, the majority of rating transitions tended to be positive both for companies of investment grade and also speculative grade ratings. In general, it can be concluded that the sample of company ratings improved over the long term.

The probability distribution of a five-year default transition matrix did not have any correlation with the probability distribution of default from two-year, three-year or four-year estimations. With such differing patterns, it can be seen that in the five-year period, using the cohort method, the probability of default is 14.29% for the A-rating category. It can be demonstrated that the probability of default in the five-year estimation is strongly influenced by the default cases of 2001.

In conclusion, the rating stability pattern for investment grade businesses showed a symmetrical relationship. Figure 6.5 illustrates that higher ratings tend to have greater stability. Likewise, the stability level for investment grade companies was likely to decline in 2002 and 2003. Nevertheless, such conditions did not endure. In 2004, the deteriorating rating rebounded strongly. However, the exception was BBB, which continued to fluctuate. Of this general distribution, one can note that during 2001–05, the most stable categories were AAA and A, whereas AAA and BBB continued to fluctuate.

Figure 6.5

Corporate rating stability level of the investment grade group, based on the cohort method

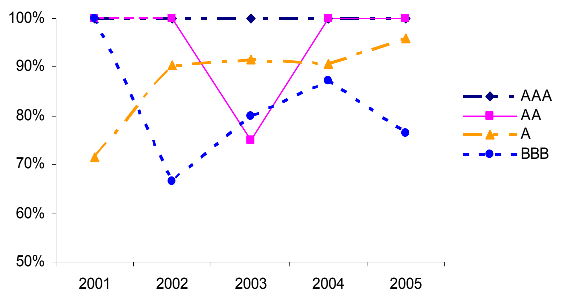
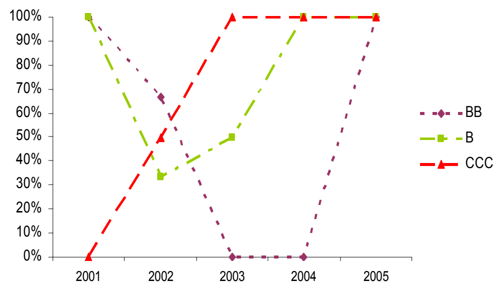


Figure 6.6

Corporate rating stability level of the speculative grade group, based on the cohort method



In contrast to the distribution achieved for investment grade companies, the distribution of the speculative rating category was unstable in nature. Instability is reflected in excessive declines and hikes over the short term (shown in Figure 6.6). However, it is important to note that the number of observations in this speculative grade was very limited; therefore, any change in the rating of one company has a great impact on fluctuations of the category as a whole.

The continuous method assuming time homogeneity

Estimations were made using a continuous approach on an annual, semiannual (2004–05), three-yearly (2003–05), four-yearly (2002–2005) and five-yearly (2001–2005) timeframe. The most salient matrices are presented here.

The five-year transition matrix (2001–05):

During 2001–05, the total number of transitions based on the continuous method assuming time homogeneity was 38, with two not-rated transitions. The probability distribution of the five-year default transition matrix was similar to the four-year pattern. Moreover, the distribution of transitional probability in 2001–05 was wider spread.

Table 2

Corporate rating transition matrix based on the continuous approach

%, 2001–05

	Number of companies at beginning of period	AAA	AA	A	BBB	BB	B	CCC	D	NR
AAA	1	100	0	0	0	0	0	0	0	0
AA	5	0	94.31	5.42	0.06	0.04	0	0.05	0.06	0.02
A	20	0	4.51	86.72	2.02	1.31	0.23	1.37	2.19	0.70
BBB	7	0	0.38	14.61	82.87	0.13	0.24	0.13	0.17	1.39
BB	0	0	0.10	5.50	27.41	41.40	1.40	13.48	10.32	0.28
B	2	0	0.03	1.55	7.70	4.94	78.33	5.18	1.29	0.07
CCC	1	0	0.56	19.19	2.59	6.82	8.99	39.50	21.43	0.11
D	3	0	0	0	0	0	0	0	100	0
NR	1	0	0.61	21.89	1.29	0.94	20.61	0.97	0.41	52.31
Total	**40**									

In terms of a symmetrical relationship between rating stability and rating quality, the estimation results for 2001–05 illustrate a similar relationship for the transition matrix of two, three and four years. The rating stability level declined in line with a drop in rating, reaching BB. Furthermore, rating B has greater stability than BB.

Transitional probability generally declined in line with the wider gap in transitional distance, although several ratings displayed a fairly high probability of migration.

After five years, the possibility of transition emerged from speculative grade to the investment grade and vice versa. However, the transition direction of upgraded ratings surpassed the downgraded ratings. This implies that the sample companies, over the long term, improved in terms of creditworthiness, although several companies also experienced a decline in credit quality.

Over the five years measured, companies also faced the probability of default or being downgraded to rating D. Even companies rated AA and A faced the possibility of default. The safest companies are the ones rated AAA. This is similar to the results of the four-year transition matrix. The probability of default increases with a decline in rating quality, except for BBB and B.

In terms of rating stability, the five-year and four-year transition matrices show that the investment grade category maintains fairly high stability. Meanwhile, the speculative rating category also displayed relatively high stability for companies rated B and C for the four-year transition matrix and rated B for the five-year transition matrix.

Corporate rating stability based on the continuous method assuming time homogeneity

The distribution of rating stability for investment grade companies is illustrated in Figure 6.7, whereas the non-investment and speculative grade categories are illustrated in Figure 6.8. From Figure 6.7, it can be seen that the investment grade generally maintains a stability level above 65%.

Rating A experienced an escalating stability trend from year to year. Meanwhile, ratings AA and BBB experienced significant fluctuations.

Figure 6.7

Corporate rating stability for the investment grade group based on the continuous method

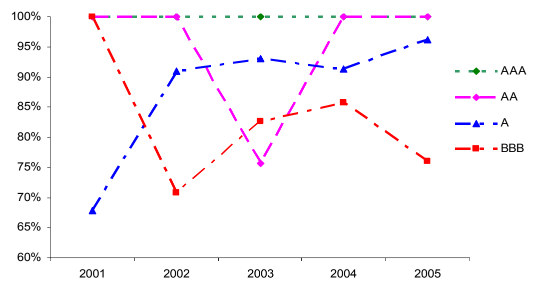
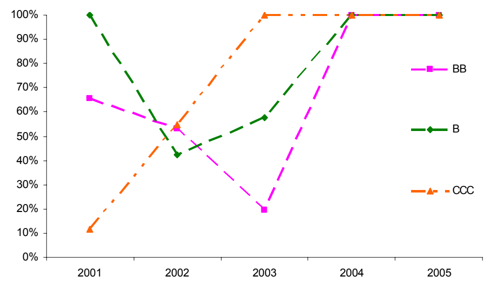


Figure 6.8

Corporate rating stability for the speculative grade group based on the continuous method



Sample companies rated AAA maintained high stability from year to year. This indicated that issuers rated AAA tend to maintain high stability and are somewhat resistant to negative market influences. However, it is noted that the number of observations for this rating was very limited and, therefore, not fully representative of market conditions. On the other hand, the most unstable rating among the investment grade is BBB with the smallest stability percentage.

Figure 6.9

Corporate rating stability for the investment grade group using various timescales

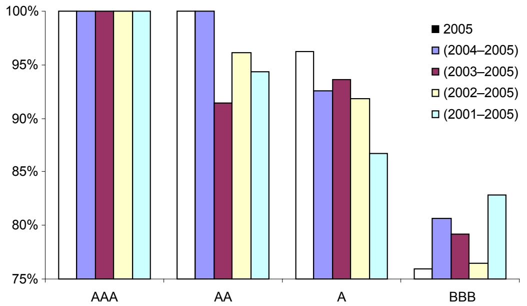


Figure 6.10

Corporate rating stability for the speculative grade group using various timescales

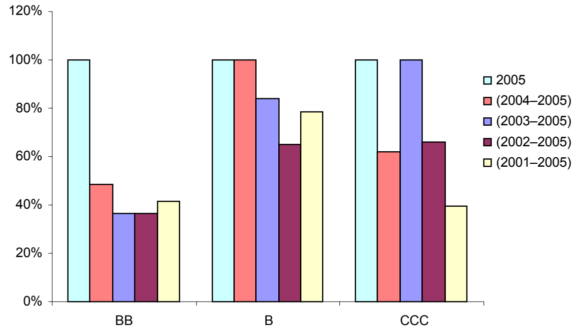


Figure 6.9 illustrates the rating stability of the investment grade category for each estimation period. For the five estimation periods, rating stability remains relatively high, always above 75%. In general, higher ratings lead to greater stability. Figure 6.9 also implies that the rating stability will continue to decline as more periods are added. Slightly different from previous estimations, the BBB rating shows fluctuations.

Rating stability of the speculative or non-investment grade category generally experienced a decline in stability as the estimation period lengthened (Figure 9.10). However, fluctuations were also visible, particularly for rating CCC.

Transition matrices for corporate bonds

Cohort method

The transition matrices to estimate bond ratings applying the cohort method in this study use annual, two-yearly (2004–05), three-yearly (2003–05), four-yearly (2002–05) and five-yearly (2001–05) timeframes. To summarise, not all matrices are presented.

The five-year transition matrix (2001–05)

During 2001–05, the number of bond rating transitions, based on the cohort method, was 22. The estimation results for 2001–05 are presented in Table 3.

Table 3

Transition matrix of bond ratings based on the cohort method

%, 2001–05

	Number of bonds at beginning of period	**AAA**	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**D**	**NR**
AAA	0	**n.a.**	0	0	0	0	0	0	0	0
AA	1	0	**100**	0	0	0	0	0	0	0
A	27	0	22.22	**55.56**	3.70	0	0	0	18.52	0
BBB	11	0	0	9.09	**81.82**	0	9.09	0	0	0
BB	2	0	0	0	50	**0**	0	0	50	0
B	8	0	12.50	12.50	0	12.50	**50**	0	12.50	0
CCC	3	0	0	0	0	66.67	0	**33.33**	0	0
D	0	0	0	0	0	0	0	0	**100**	0
NR	0	0	0	0	0	0	0	0	0	**0**
Total	**52**									

The probability distribution for the five-year default transition matrix was similar to the four-year distribution. Moreover, the distribution of transitional probability for period 2001–05 showed a larger default probability.

The estimation results for 2001–05 showed no relationship between rating stability and rating level. A falling level of stability did not correlate to the rating regression. Rating BBB is more stable than A.

In addition, and not shown in Table 3, transitional probability declines as the magnitude of transitional distance widens. It is interesting to note that the probability of upgrading a CCC rating to BB is 66.67% after five years. In terms of rating stability, the five-year and four-year transition matrices indicate that investment grade ratings have a higher probability of upgrading than downgrading.

The speculative grade rating category (BB and B) has a tendency to migrate, with a migration probability to BBB of 50%, to A of 12.5% and to AA of 12.5%.

The stability distribution of sampled bond ratings of investment grade is illustrated in Figure 6.11. The figure shows the AAA rating as the most significant mover, with a stability level from 0% to 100%. However, this was due to no sample bond data found with an AAA rating in 2001 and 2002. An AAA-rated bond only appears in the 2003 sample, where the stability level remained at 100%.

Figure 6.11

Stability of investment grade bond ratings based on the cohort method

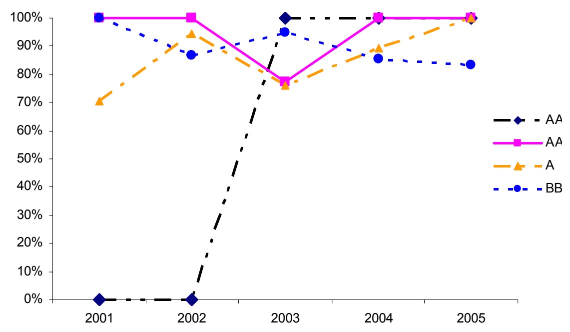
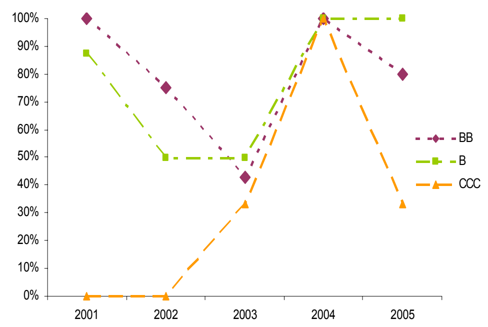


Figure 6.12

Stability of speculative grade bond ratings based on the cohort method



The transition distribution of speculative grade rating stability can be seen in Figure 6.12. It is clear that speculative rated bonds are generally unstable compared to investment grade bonds (Figure 6.11). The speculative rating tends to have a high fluctuation rate.

Figure 6.12 shows that, in contrast to BB and B ratings, which experienced a high probability of downgrade in 2001–03, bonds rated CCC during the same period experienced a relatively high probability of upgrading. However, every level of bond rating in the speculative grade deteriorated.

Continuous method assuming time homogeneity

The five-year transition matrix (2001–05):

In the given period, the total number of bond rating transitions based on the continuous method was 29 with two not rated. The estimation results for 2001–05 are presented in Table 4.

The stability of bond ratings during 2001–05 was sufficiently high, at around 88–100%, except for the CCC rating at only 50.58%. It is due to its junk bond or speculative grade status, implying a low quality bond with a relatively high default probability. Since investment grade bonds are stable, such bonds are not speculative but for investment. On the other hand, speculative grade bonds with high rating fluctuations are often used by speculators to generate high returns.

Table 4 illustrates that a CCC rating has a transition probability to upgrade to a B rating of 22.48%, to a BB rating of 23%, a BBB rating of 1.72% and an A rating of 0.03%. However, the CCC rating has a default probability of 1.32%.

The transition matrix for 2001–05 did not return a symmetrical distribution. The farther from the diagonal, the magnitude of rating transition varied and the probability did not always decline. Even from the stability side (diagonal side), there was no consistent distribution. Lower bond quality leads to less stability.

Regarding the five-year transition matrix, only A- and BB-rated bonds (investment grade category) displayed a small transitional probability towards the speculative grade. In addition, all speculative grade bonds (BB, B and CCC) show a positive transitional probability to become investment grade.

Table 4

Transition matrix of bond ratings based on the continuous method

%, 2001–05

	Number of bonds at beginning of period	AAA	AA	A	BBB	BB	B	CCC	D	NR
AAA	0	100	0	0	0	0	0	0	0	0
AA	1	0	100	0	0	0	0	0	0	0
A	27	0	7.14	86.76	0.99	0	0.01	0	5.10	0
BBB	11	0	0.18	4.54	93.58	0.03	1.47	0.04	0.16	0
BB	2	0	0	0.14	5.82	87.96	0.05	0	6.03	0
B	8	0	0	0.15	6.13	3.77	82.29	4.43	3.23	0
CCC	3	0	0	0.03	1.72	23.87	22.48	50.58	1.32	0
D	0	0	0	0	0	0	0	0	100	0
NR	0	0	0.04	1.22	39.66	6.85	6.95	26.98	0.30	18.01
Total	**52**									

Bond rating stability using the continuous homogenous method

The stability of bond ratings from 2001–05 can be analysed separately between investment grade and speculative grade respectively. The stability of investment grade bonds is higher than speculative grade bonds. Figure 6.13 illustrates that investment grade bond stability is around 70–100%. Furthermore, from Figure 6.14 it can be determined that speculative grade bond stability is around 20–100%. The graph showing investment grade bonds was flatter compared to the speculative grade. Among investment grade bonds, AAA rated are the most stable, followed by AA, BBB and A. The highest quality rating is AAA, which also represents the most stable. The stability of BBB outperforms A, which is illustrated by the flatter line compared to line A. However, the stability trend of A increases from 2001 to 2005. This is contrasted against the BBB rating, which regresses.

Figure 6.13

Stability of investment grade bond ratings based on the continuous method

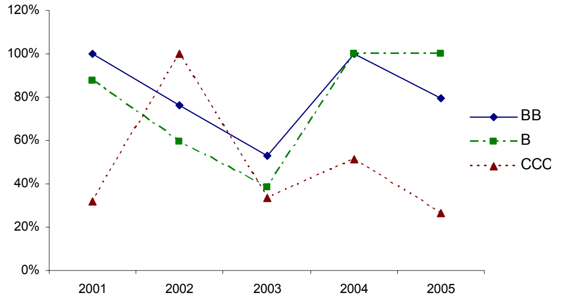
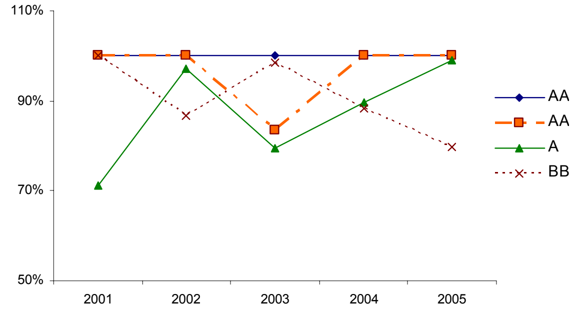


Figure 6.14

Stability of speculative grade bond ratings based on the continuous approach



The stability of bond ratings from 2001–05 fluctuated wildly, as shown by increasing and decreasing shifts on the graphs. In terms of the speculative grade, the BB rating is the most stable followed by B and CCC ratings. From Figure 6.14, it can be concluded that the lower the bond rating quality, the lower the stability level will be.

7. Conclusion of estimation results and policy implications

7.1 Rating activity and rating drift

The analysis of corporate credit quality is a major consideration in terms of investment evaluation. It is in the interest of investors to be aware of credit quality since no investor wishes to suffer a loss due to a decline in rating quality. Two indicators that can be monitored to evaluate credit quality are rating activity and rating drift. These two indicators can highlight rating movement trends and can provide an indication of the creditworthiness of bond issuers.

In brief, from the analysis results it was concluded that the sample of bond issuers improved their creditworthiness over time. This was evidenced by a decline in the percentage of downgraded companies and bonds as well as a rise in upgrades.

In addition, it was also concluded that the percentage of rating activity of the sample of companies and bonds during 2001–05 decreased relatively. However, the current trend of rating activity is improving, which is reflected by an increase in rating drift. This implies that the creditworthiness of the sample of companies and bonds has improved over the past few years.

Estimation results of the rating transition matrix

The transition matrices were constructed using two approaches, the cohort method and the continuous method with time homogeneity. The cohort method is based on Jafry and Schuermann (2004), and the continuous method is adapted from the study by Lando and Skødeberg (2002).

As mentioned by Lando and Skødeberg (2002), the cohort method offers a simple estimation process. However, the method has a very rigid assumption that time is discrete; therefore, rating activity cannot be analysed holistically. The method considers the rating position or company bonds at the beginning and end of a period only, excluding the dynamic process found within the period.

Estimations using the continuous method provide more efficient results than the cohort method. Furthermore, the method also facilitates indirect estimations of a rating in a sequential way. Additionally, the method facilitates the construction of transition matrices that are able to accommodate the dynamic factors of rating activity throughout the period, not just at the beginning or the end. The cohort method produced a transition matrix with an uneven probability distribution concentrated around the diagonal. Meanwhile, estimations using the continuous method are best for corporate or bond ratings, producing transition matrices with a more spread probability distribution. This spread facilitates the probability of distant migration far from the diagonal (extreme transition), even to default without direct transition to that rating, and is possible through indirect transition through other ratings. The type of probability distribution shown is primarily illustrated by the estimation results for a period longer than one year. In addition, estimations using the cohort method failed to show the relationship between stability and rating; indicated by the rating stability level not declining in line with the drop in the rating level. This mainly occurred for estimation results using a one-year period. Meanwhile, several estimation results for periods of longer than one year indicated a symmetrical relationship between rating stability and rating level, but only when investment grade ratings were used.

Estimations using the continuous method showed the contrary. Most estimations, for various time periods, indicated consistent results: that there is a symmetrical relationship between rating stability and rating level. This distribution was mainly found at the investment grade rating. The stability level of the rating varied, but was generally above 65%.

Ratings in the speculative grade fluctuated and did not show a consistent distribution due to a limited number of samples, both corporate and bonds. Thus, a one-sample transition in the speculative grade category had a significant impact on the migration probability distribution.

In terms of the rating migration trend, estimation results using cohort and continuous methods provided relatively consistent results. Rating migration tends to upgrade, which is consistent with the analysis conducted on rating activity and rating drift.

It can be concluded that using the continuous method, assuming time homogeneity, produced a transition matrix, which is more efficient. The matrix indicated the possibility of rating migration where historically it had rarely occurred. For example, to experience default through an indirect default mechanism.

In addition, the estimation results for both the cohort method and the continuous method indicated that the sample of companies and bonds improved in creditworthiness over time. This was expressed by the rating migration trend, which leaned towards higher ratings. However, the major constraints of this study were the limited number of periods and samples. This is also true for rating activity variation, which is shown by the limited number of rating transitions.

Such a brief sample period prevented any long-term transition matrix estimations and, unfortunately, the timescale did not date back far enough to the Indonesian recession post Asian crisis. Consequently, the limited number of samples caused a one-rating transition to have a substantial impact on the probability distribution.

This mainly affected samples in the speculative grade category. This prevented any creditworthiness analysis of bond issuers in this category.

References

Ahmed, Sarfaraz et al (2004): "Use of transition matrices in risk management and valuation", A Fair Isaac White Paper.

Bank for International Settlements. (2001). "Basel II: The New Basel Capital Accord – Second Consultative Paper", January.

Bank for International Settlements (2005): "Zero-coupon yield curves: technical documentation", BIS Papers no 25.

Basel Committee on Banking Supervision (1999): "Analyzing rating transitions and rating drift with continuous observations", Journal of Banking and Finance 26, pp 423–44. www.elsevier.com.

Carty, L., and J. Fons. (1993). "Measuring changes in corporate credit quality", Moody's Special Report, Moody's Investors Service, New York.

Israel, R.B. et. al. (2001). "Finding Generators for Markov Chains via Empirical Transition Matrices, with Applications to Credit Ratings", Mathematical Finance 11 (2): 245–265.

Kryzanowsky, L., and J. Menard. (2001). "Migration Behavior of Long-Term Bond Ratings of Canadian Corporate Issuers", Canadian Investment Review, Fall.

McNulty, Cynthia and Ron Levin (2000): “Modeling credit migration”, JP Morgan Securities.

Rorres, C. and H. Anton. (1987). “Elementary Linear Algebra”, New Jersey. John Wiley & Sons. ISBN13: 9780471851042.

Jafry, Y. and T. Schuermann. (2003). “Metrics for Comparing Credit Migration Matrices”, Wharton Financial Institutions Center Working Paper No. 03-09. Available at SSRN: http://ssrn.com/abstract=394020 or DOI: 10.2139/ssrn.394020.

Jafry, Y. and T. Schuermann. (2004). “Measurement, estimation and comparison of credit migration matrices”, Journal of Banking & Finance 28 (11):2603-2639.

van Deventer, D and K Imai (2003): *Credit risk models and the Basel Accords: the Merton model and reduced form models*, John Wiley & Sons.

van Deventer, Donald R and Xiaoming Wang (2003): “Advanced credit model performance testing to meet Basel requirements”, in *The Basel Handbook – A Guide for Financial Practitioners*, RISK Publications.

Van Landschoot, Astrid (2005): *Transition probabilities and asset correlation: structured products versus corporate*, McGraw-Hill.

Violi, Roberto (2004): “Credit ratings transition in structured finance”, CGFS Working Group on Ratings in Structured Finance.