Through-the-Cycle Ratings Versus Point-in-Time Ratings and Implications of the Mapping Between Both Rating Types

BY REBEKKA TOPP AND ROBERT PERL

The two philosophies of ratings, one that includes cyclical effects and the other that doesn’t, are mirrored by the two different rating types commonly known as point-in-time (pit) and through-the-cycle (ttc). Point-in-time ratings try to evaluate the current situation of a customer by taking into account both cyclical and permanent effects. In contrast, through-the-cycle ratings focus mainly on the permanent component of default risk and are nearly independent from cyclical changes in the creditworthiness of a customer. In this paper we give a review of the characteristics of both rating types and examine whether these properties can actually be observed in practice. In this context we present the results of an analysis of Standard & Poor’s rating data, which show that the ratings, though being through-the-cycle, still vary in accordance with the business cycle. Another concern of this paper is the widespread practice to map ‘external’ through-the-cycle ratings to ‘internal’ point-in-time ratings, with the purpose to enrich or validate a financial institution’s internal rating database. We show that in doing so financial institutions severely misrepresent customers’ risk profiles and under- or overestimate costs in connection with credit pricing or capitalization. We confirm our theoretical considerations by calculating pricing quantities when using one or the other rating information.

I. INTRODUCTION

Ratings are an important part of today’s banking business. Since the establishment of the New Basel Accord in 2004 financial institutions can use ratings directly to determine the size of their capital buffer. Ratings also play an important role in credit decisions, the pricing of credits, and the proper management of a financial institution portfolio’s risk profile.

There has been much discussion about the properties a rating should exhibit in order to be a useful risk management tool. Ratings can be constructed by using a variety of information which can be either borrower specific, characteristic of certain industries (so-called permanent effects) or referring to the current state of the business cycle (cyclical effects).

The two common philosophies of ratings, one that includes cyclical effects and the other that doesn’t, are mirrored by the two different rating types commonly known as point-in-time (pit) and through-the-cycle (ttc). Point-in-time ratings try to evaluate the current situation of a customer by taking into account both cyclical and permanent effects. For this reason they are known to react promptly...
on changes of the customer’s current economic situation. In contrast, through-the-cycle ratings focus mainly on the permanent component of default risk and are said to be nearly independent from cyclical changes in the creditworthiness of a customer. As a direct consequence, these ratings are much less volatile over time.

This paper investigates two relevant and new research questions: The first one deals with the cyclicality of agency ttc ratings which is examined by analyzing Standard & Poor’s (S&P) rating data. Our results show that these ratings, though being through-the-cycle, still vary in accordance with the business cycle, especially when considering certain industry branches. The second research question concerns the wide spread practice in the financial industry to map ‘external’ ttc ratings to ‘internal’ pit ratings, with the purpose to either enrich or validate an institution’s internal rating database. We show that in doing so financial institutions severely misspecify their customers’ risk profiles and under- or overestimate, depending on the state of the economy, costs in connection with credit pricing or capitalization. We confirm our theoretical considerations by calculating pricing quantities when using one or the other rating information.

The paper proceeds as follows: In Section II we discuss the properties of through-the-cycle and point-in-time ratings. In Section III we analyze a representative ttc dataset by using a history of S&P ratings and checking whether their properties fit to those presented in Section II. In Section IV we discuss the consequences of mapping ttc ratings to pit ratings, and in Section V we show that it makes a big difference in financial institution’s pricing calculations whether to follow the ttc or pit approach. Finally, some concluding remarks are given in Section VI.

II. CONSTRUCTION AND PROPERTIES OF THROUGH-THE-CYCLE AND POINT-IN-TIME RATINGS

This section deals with our first research question, the cyclicality of ttc ratings. It gives an overview of the construction of the two rating methodologies, reviews their theoretical properties and addresses the question whether the theoretical properties of ttc ratings can actually be observed in practice.

The ttc methodology is mostly applied by rating agencies like Moody’s or S&P. Their approach consists in assessing the default risk of a firm in its worst point of the credit cycle or industry cycle – the so called stress scenario. In order to specify the stress scenario rating agencies usually conduct a stress test by using historical default rates in the respective industry.

Within the ttc methodology, rating changes only happen if some situation occurs which requires an adjustment of the stress scenario. For example, a decision by the borrower that fundamentally alters its risk, a change in the nature of the borrower’s industry, or a recognition by the agency that its stress scenario is inappropriate.
Changes in the credit cycle, though, do not lead to rating changes since they are ‘through-the-cycle’, that is, mostly independent from the credit cycle.

In contrast, most financial institutions rely on pit ratings which are constructed by using quantitative financial information like balance sheet information, qualitative factors like management qualities, and, most importantly, information about state of the economic cycle. These information are then transformed into rating categories by applying statistical procedures like scoring models. Since pit ratings include cyclical information, their validity is only short to medium term and mostly valid over a one year horizon only.

One of the disadvantages of the ttc approach is that if the agency’s stress scenarios are frequently materially different from the firm’s current condition, then in good times the assigned ratings are too conservative. Or, if a firm’s current condition is already worse than the stress scenario, e.g. for firms with ratings of high risk, then the rating may be too optimistic. As a consequence, ttc ratings are said to have a low default prediction in the short run and there is empirical evidence that the default probabilities published by the rating agencies do neither fit the mean probabilities of default of the stress scenarios nor the mean of the actually observed firms’ default probabilities, see for example the results in Löffler (2002, 2004).

On the other hand, ttc ratings are much more stable over time than pit ratings. The recent financial crisis shows impressively the strong connection between internal ratings and the capital endowment of financial institutions. In such cases, pit ratings force volatile capital underlyings and can have procyclical effects. In economic downturns pit ratings deteriorate and require higher capital requirements, which increase the costs for the lender and therefore make credits dearer. The financing conditions of firms worsen and the pit ratings deteriorate further. This can end up in a self exciting process and enforce the economic downturn. In economic upturns the reverse process can happen. In both cases ttc ratings can dampen such processes and account for better financial stability.

Another advantage of ttc ratings is that the low volatility supports internal processes of financial institutions. Very often competence rules of a financial institution depend on ratings and the responsibilities change with the rating grade. If the applied ratings are very volatile then these changes happen very often and make the consistent management of a customer difficult.

There has been extensive academic research on whether the nature of agency ratings is in fact as being claimed by them. For example, agencies claim that all customers assigned to the same rating class are homogeneous with respect to their probability of default. This would imply that firms of the same rating class have the same probability distribution with respect to their future rating development: given a certain rating status the probability for an up- or downgrade should be the same for all firms regardless of the observed rating movements in the past. Nevertheless, several empirical studies prove the existence of a so called rating momentum where e.g. firms with a history of downgrades experience a higher probability of further

Agency ratings are also said to preserve the rankings of their rating classes even if the probability of default in each rating class might change during the course of time. This would mean that e.g. a customer rated BBB will always have a better credit quality than a customer rated C, regardless of the state in the credit cycle. Though, in our analysis of default rates derived from S&P’s CreditPro database we show that the ranking of the rating classes changes during the credit cycle and thus the comparability of the ratings is doubtful in certain situations.

Also the independence from cyclical movements of agency ratings has been under investigation. This should be reflected both by their default rates and migration probabilities over time. Nevertheless, numerous studies show that there exists cyclical variation in default and migrations probabilities of through-the-cycle ratings, see for example, Wilson (1997a, 1997b), Nickell, Perraudin and Varotto (2001), Kavvathas (2001), Bangia Diebold, Kronimus, Schagen and Schuermann (2002), Fledelius, Lando and Nielsen (2004), Koopman, Lucas and Monteiro (2005), Koopman, Lucas and Daniels (2005), Koopman and Lucas (2005), Koopman, Lucas and Klaassen (2005), Koopman, Kräuss, Lucas and Monteiro (2006) or Frydman and Schuermann (2006). Further evidence for the dependence of through-the-cycle ratings on cyclical movements is added by our analysis of S&P’s CreditPro database.

### III. RESULTS FROM THE ANALYSIS OF S&P’s CREDITPRO DATABASE

For our analyses we used S&P’s CreditPro6.0 database containing rating information of firms of different industries as well as financial institutions and insurances over an extensive time horizon. Most firms in the database are US-based though in recent years also European firms entered more frequently. Our analysis includes only US counterparties in order to avoid biases due to country-specific effects. We looked at their rating histories in the time interval between January 1986 and December 2006. In this time period the rating and industry distribution per year is reasonably stable so our analysis cannot be distorted by biased data samples. Furthermore, during this time period there are sufficient data both regarding the number of defaults and the total number of observations in the considered rating classes.

Our analysis sample consists of a total of 7355 firms. For these firms the rating and industry distributions can be assumed to be identical between the years. The
stability of these two parameters guarantees an unbiased analysis of the default rates in the different rating classes and industries.

**Analysis of Default Rates in Sub-Investment Rating Grades**

We calculated default rates by relating the number of defaulted firms to the total number of firms in a rating class and industry class, respectively. While in the calculation of the number of defaults per year no assumptions are made, the calculation of the number of firms per year base on the following premises:

1. If a firm’s last rating is dated before the year of 2006 and this firm has not defaulted yet, then this rating will be considered valid for the time period up to 2006.
2. If a firm’s last rating is ‘Default’ then this firm counts for the number of firms of the rating class it belonged to before the default occurred and in the year were the default occurred. Afterwards this firm is not considered anymore.
3. For firms being rated more than once a year the latest rating of the year is considered as being representative for that year.
4. ‘Not Rated’ entries are generally not included in the analysis since it is not clear whether this means that a firm has probably defaulted, been merged or just has no more need to be publically rated.

The following Figure 1 displays the resulting default rates in the time period between 1986 and 2006. Since there is a too small number of defaults in

![Figure 1: Default Rates (in %) of sub-investment rating classes.](image-url)
investment grade rating classes and a too small number of firms in the worst sub investment classes (CC and C) we constrain our analysis to rating grades B+ up to CCC−.

It can be observed that the curves of several rating classes cross at various points in time: CCC− and CCC in 1986, 1997, 1998, 2000 and 2001, CCC and CCC+ in 1987, 1990, 1991, 1994 and 2003, B− and CCC in 1987 and 1990, B− and B in 1989, 1992 and 1993 and B und B+ in 2002 and 2006. Although there is no complete overlap of curves there is still evidence that a stable ranking between them is not given during the course of time. Though no empirical considerations are possible for investment grade rating classes it seems doubtful whether a clear differentiation between e.g. AAA and AA rating grades with respect to default rates is given.

In a second analysis we compared the course of the default rates of each rating class with the course of the US-GNP, a well accepted indicator for the economic cycle in the US. The following Figure 2 shows the results:

Figure 2: Rating class-specific default rates and US-GNP.
Through-the-Cycle Ratings Versus Point

Table 1: Correlation of default rates and US-GNP

<table>
<thead>
<tr>
<th></th>
<th>B+</th>
<th>B</th>
<th>B−</th>
<th>CCC+</th>
<th>CCC</th>
<th>CCC−</th>
</tr>
</thead>
<tbody>
<tr>
<td>GNP</td>
<td>−0.78</td>
<td>−0.51</td>
<td>−0.70</td>
<td>−0.70</td>
<td>−0.13</td>
<td>0.12</td>
</tr>
</tbody>
</table>

It can be observed that the default rates of rating classes B+ up to CCC+ move accordingly to the business cycle, that is, default rates fall in times of high GNP and rise in times of low GNP. This behavior cannot be seen in the rating classes CCC and CCC−. The Spearman’s correlation coefficients confirm this observation (see Table 1). A possible reason for the uncyclical behavior of the latter two rating classes could be that the number of firms in these classes is too low in order to produce meaningful default rates. Nevertheless, the observation that some rating classes move in accordance with the business cycle casts doubt on the claim that agency ratings do not show cyclical behavior during the course of time.

Analysis of Default Rates in Different Industries

We also calculated industry-specific default rates in order to understand the behavior of counterparty defaults in different industry types. Because of the small number of real estate counterparties in the data sample we exclude this industry from our analysis. Again we use US-GNP as a proxy for the state of economy during the given time period. The graphs in Figure 3 display the course of the default rates and the GNP for each of the considered industry.

Table 2: Correlation of industry-specific default rates and US-GNP

<table>
<thead>
<tr>
<th>Aerospace, Automotive, Capital Goods, Metal</th>
<th>Energy and Natural Resources</th>
<th>Forest &amp; Building Products, Homebuilders</th>
<th>Health Care, Chemicals</th>
</tr>
</thead>
<tbody>
<tr>
<td>US-GNP</td>
<td>−0.58</td>
<td>−0.71</td>
<td>−0.11</td>
</tr>
<tr>
<td>High Tech, Computers, Office Equip., Insurance</td>
<td>Leisure Time, Media Telecommunications Transportation Utility</td>
<td></td>
<td></td>
</tr>
<tr>
<td>US-GNP</td>
<td>−0.61</td>
<td>−0.13</td>
<td>−0.58</td>
</tr>
</tbody>
</table>

It can be observed that most industries’ default rates vary according to the economic cycle which is also reflected by Spearman’s correlation coefficients in Table 2. Obviously for industries like the consumer and service sector, the building products industry or the high technology and computer industry, which are generally known of being susceptible to changes in the economic cycle, the observed default rates vary in accordance with the state of economy. In contrast, for
industries like insurance or energy which are less susceptible to current conditions of the economy, the default rates move mostly independently from the credit cycle. This observation casts further doubt on the assumption of rating class homogeneity of agency ratings since due to the differently strong cyclicality of firms of different industries, the agencies’ claim of homogeneous default probabilities within each rating class does not hold in practice.

Figure 3: Industry-specific default rates and US-GNP.
Summarizing the results of this section we conclude that default rates from ratings constructed by rating agencies like S&P do not show the typical behavior of through-the-cycle ratings: they do not always have a stable ranking between them and they do not generally move independently from the business cycle, especially when considering their industry classification.

IV. CONSEQUENCES OF MAPPING POINT-IN-TIME TO THROUGH-THE-CYCLE RATINGS

Despite the detected cyclicality of some part of S&P ratings, we assume that agency ratings are more stable over the business cycle than the financial institutions’ internally estimated point-in-time ratings.

In this section we want to show the effects of the different rating methodologies on risk management issues of financial institutions and the consequences which arise when a mapping between the two methodologies is applied. In practice, financial institutions do not always have enough data for parameterization of risk management systems. As we will show, one would need a specific rating matrix for every different rating system for pricing or capital requirement calculations. Therefore at least several hundreds of customers and rating years were needed, which is impossible in practice in many cases - e.g. aircraft finance. This gap is filled either with external information (e.g. external ratings) or internal data (e.g. from a different rating tool. In economic literature mappings are used, for example, by Altman and Rijken (2005), Löffler (2004), Segoviano and Lowe (2002). Mapping problems were examined by Carey and Hrycay (2001) and Treacy and Carey (1998).

![Figure 4: CT-path of through-the-cycle and point-in-time rating systems.](image)

Suppose there is a portfolio which is rated both point in time and through the cycle. Figure 4 shows the time paths of the central tendency ($CT_p$) of this portfolio, i.e. the mean of the one year default probabilities (PD) in the portfolio. The straight line is the ‘true’ long-term CT, the dashed line the CT of the ttc methodology reflecting mainly the permanent component, and the solid curve shows the CT-development of the pit system, thus being more volatile.
Suppose that at the beginning a ttc rating system and a pit rating system are calibrated at the same level (black dot in Figure 4). As can be seen in Figure 4 even in this case of an identical starting point the behavior of ttc and pit ratings result in different time paths of the central tendency, i.e. the average default rate of the portfolio for every point in time. Given this observation the common practice of mapping pit ratings to ttc ratings is inappropriate over time. Even in the case where the long-term CT of the point-in-time and the through-the-cycle rating match, the one year PDs are not comparable because of different cyclicality of the rating systems.

The same effect can also be seen in migration matrices constructed from pit and ttc ratings. The migration matrices for a pit rating system should be more volatile than those for a ttc rating system. This means that a ttc matrix has more probability-mass on the diagonal than a pit matrix, i.e. the probabilities of persistence are much higher. Thus, the choice which type of migration matrix to use in risk management is crucial and if the migration matrix doesn’t fit the rating system’s behavior, the consequences can be severe as shown in the following.

![Figure 5: Forecast of point-in-time CT vs. through-the-cycle CT.](image)

Suppose we are at the end of a recession scenario and we are using a pit rating system, but our migration matrix is based on a ttc methodology. In this case the forecast of the behavior of the portfolio reflected in the time path of the CT is the dashed line in Figure 5. In this case we would overestimate the future CT (dotted line). On the other hand, if we are at the end of a boom period, we would underestimate the future CT systematically.

The same holds if our rating system is ttc, but the calculated migration matrix is pit. In this case we would systematically underestimate the average CT if we are at the end of a recession.

It is obvious that the effect of under- or overestimation of the correct rating development depends on the time horizon of the forecast and does not increase automatically with growing forecast horizon. Furthermore in the long run, i.e. over a credit cycle, the long-term CTs of both rating systems should match.

The systematic bias in forecasting the CT is reproduced in every risk instrument using default probabilities as an input factor. As an example, we show in the next section the impacts of using mismatching rating philosophies in risk adjusted pricing.
V. IMPLICATIONS OF USING MISMATCHING RATING METHODOLOGIES FOR PRICING ISSUES

Our previous discussion showed that a sensible risk management system needs a consistent rating and migration matrix methodology. To demonstrate to what extend biases can occur we conducted a small simulation study using risk adjusted pricing as an example.

Starting with a migration matrix of S&P we constructed three additional, more volatile migration matrices. For this purpose we reduced the probabilities of persistence on the diagonal of the matrix for a certain amount and distributed them proportionally to the non-diagonal elements of the matrix. As a result we got four different migration matrices representing a ttc rating system, a pit rating system, a migration matrix for situations of economic expansion and one for recession conditions (see Appendix A). The construction of these matrices is described in the following.

The ttc matrix is derived from the S&P Credit Pro Database using data from January 1998 to December 2003. From this matrix the pit transition matrix was constructed by shifting 25% of the probability of each diagonal element proportionally to the left and right of each row. Thus, the ratio of the weights above the diagonal to those below stays the same as before.

For the construction of the boom matrix we shifted 25% of each S&P diagonal entry proportionally to the entries below the diagonal. The upper triangular matrix remains unchanged. For the construction of the recession matrix we shifted 25% of each S&P diagonal entry proportionally to the entries above the diagonal. Now the lower triangular matrix remains unchanged.

For each of the four transition matrices we calculated the Expected Loss (EL) or Standard Risk Costs (SRC), an important quantity in risk adjusted pricing:

$$EL = \sum_{i=1}^{T} \frac{LGD \cdot EAD_i \cdot PD_i}{(1 + r)^i}$$

for each rating class and maturities of up to $T = 10$ years, EAD the Exposure at Default, LGD the Loss Given Default of 66%, and $r$ the risk free discount rate of 3.5%. The cash flows are assumed to be uniformly distributed over the payment dates $i$, $EAD_i = EAD = 185.000$ EUR. For the estimation of the PDs for time horizons bigger than 1 year we used a well known approach, the so called risk structure curves: The risk structure curves reflect the cumulative PDs for a specific rating grade over a specific time horizon $i$ and are constructed by multiplying the one year PD vector $i$-times with the migration matrix.

Looking at the mid SRC in Fig. 6, calculated as the mean over all rating categories per maturity, it is obvious that there are large differences among the calculated amounts of SRC depending on the underlying migration matrix. All SRC curves increase with maturity. The relation between the SRC of the pit matrix to that of the ttc matrix is approximately 1.4. The biggest difference can
be observed between the recession SRC curve and the boom SRC curve which ranges from 1.6 to 2.0.

This means that in our example the SRC amounts are on average 1.4 higher if we calculate the SRC using a pit migration matrix instead of a ttc matrix. If we use a recession matrix and compare it to the SRC resulting from a boom matrix the risk amount is 1.6 to 2.0 higher.

The differences are even larger if we look at the SRC calculated as the mean over the maturities for each rating grade (see Fig. 7). The SRC from the pit matrix are 1.1 (CCC) to 4.3 (AA+) times higher and overall on average 2.3 times higher than those from the ttc matrix. The same can be observed for the comparison of recession and boom SRC with an average relation of 4.7 (minimum 1.3 for CCC, maximum 13.7 for AAA). Thus, if we use the recession matrix to calculate our

\[\text{Figure 6: Average standard risk costs per maturity.}\]

\[\text{Figure 7: Average standard risk costs per rating classes.}\]

\[\text{For reasons of visibility the y-axis is a log scale}\]
SRC but are in a boom period, we would get 9.3 times higher SRC for a AA+ deal than actually necessary to cover the risk costs.

These effects do certainly not only depend on maturity and rating grade but also on the cash flows structure. Since the SRC differences increase with maturity, higher cash flows in the future imply ceteris paribus a greater divergence in SRC amounts.

In summary, our results show that the usage of migration matrices based on different assumptions may lead to huge differences in standard risk costs. Thus, using an inappropriate migration matrix leads to either under- or overestimating the risk costs and, therefore, either undercovering risk or losing customers due to inappropriate high prices. Since we only compared average values it is obvious that for specific rating grades and specific maturities the deviations of the SRC can be even higher.

VI. CONCLUSIONS

In this paper we reviewed the differences between point-in-time (pit) and through-the-cycle (ttc) ratings and provided new insight into the actually observed properties of agency ratings. Though agencies claim to provide ratings that are independent of cyclical effects our empirical analyses of S&P’s rating data showed that this does not hold in general but very much depends on rating class and industry classification of a firm. Furthermore we showed that rating classes change their ranking within the sub investment grades over the business cycle and thus it seems doubtful whether a clear differentiation between all rating grades with respect to default rates is always given.

In our second research question we discussed the consequences of mapping pit ratings to ttc ratings, a common practice in financial institutions, and showed that it leads to systematic over- or underestimation of default probabilities. We show that the impact on risk management is quite strong using pricing decisions as an example: it leads to systematic under- or overestimation of the standard risk costs, depending on which part of the credit cycle is active during the mapping process and how the credit cycle evolves during maturity of the considered assets. In our example the deviations are biggest in the good rating classes. This is important, because these are the main risk categories where financial institutions are usually doing their business.

Since competition on the markets has constantly become stronger over the last years and the latest crisis of the financial system has revealed deficiencies in most financial institutions’ risk management, it should be a main concern for financial institutions to understand all aspects of risk in their portfolio and establish a consistent risk management system including matching rating systems and rating migration information.

VII. REFERENCES


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**VIII. NOTES ON CONTRIBUTORS**

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