

## Special Comment

# Moody's Credit Policy

June 2008

## Testing The Cross-Sectional Power Of The Credit Transition Model

### Summary

In this paper we present the results related to the cross-sectional power of the Credit Transition Model as summarized by the *accuracy ratio*. We have tested the ability of the model to predict, in the cross-section, *default*, *withdrawal*, *downgrade*, *upgrade*, *stability*, *fallen angel* and *rising star* transitions. We have examined the model's performance by region, industry, rating category and forecast horizon. This Special Comment includes only a subset of all these results; complete statistics may be found at

[http://www.moodys.com/cust/content/Content.ashx?source=StaticContent/FreePages/Products and Services/Downloadable Files/Back\\_Testing.zip](http://www.moodys.com/cust/content/Content.ashx?source=StaticContent/FreePages/Products%20and%20Services/Downloadable%20Files/Back_Testing.zip)

While it is difficult to draw many broad conclusions, our findings include:

- Accuracy ratios are highest for the *default* transition, followed by *fallen angel* and *rising star* transitions. *Upgrade* and *downgrade* predictions are somewhat less powerful, followed by *withdrawal* and *stability*.
- For all but the *stability* measure, accuracy ratios decline with the forecasting horizon.
- Performance across regions – Global, North America and Europe – is comparable, through in almost all cases the model is more accurate in the European portfolio.
- Performance is fairly stable across industries.

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### Analyst Contacts:

New York 1.212.553.1653

#### Albert Metz

Vice President-Senior Credit Officer

#### Nilay Donmez

Product Strategist



Moody's Investors Service

## Testing The Cross-Sectional Power Of The Credit Transition Model

### Introduction

Moody's Credit Transition Model (CTM) provides forecast transition probabilities for individual issuers over variable horizons. These cover not only the probabilities of transitioning to all the rating states, but also to the *default* and *withdrawal* states. The performance of the model can be evaluated along at least two dimensions, the *time-series* power and the *cross-sectional* power. By "time-series" we mean the ability of the model to correctly predict how an aggregate rate, for example the default rate, changes over time. By "cross-section" we mean the ability of the model to predict at a point in time which issuers are more or less likely to default. These two questions are related but logically quite distinct, and it is possible for a model to perform well in one sense and poorly in the other.

This Special Comment serves as a guide to understanding the cross-sectional power of CTM. How well does it identify those issuers that are more likely to default from those that are less? Of course, since the model predicts all rating transitions, we can also ask how well it distinguishes those more at risk of downgrade, or upgrade, or withdrawal. Going even further, since the model assigns probabilities to future rating *levels*, we can explore its ability to distinguish which issuers are more at risk of becoming a fallen angel or a rising star.

Moody's has performed extensive back-testing of the Credit Transition Model's cross-sectional power. We have conducted this analysis by region, initial rating category, industry and forecast horizon. The result is an exhaustive set of performance statistics which may be reviewed, only a subset of which is presented below. This Special Comment is intended to provide examples of model performance and the necessary interpretation of the results. For the complete set of performance statistics, please go to [http://www.moodys.com/cust/content/Content.aspx?source=StaticContent/Free Pages/Products and Services/Downloadable Files/Back\\_Testing.zip](http://www.moodys.com/cust/content/Content.aspx?source=StaticContent/Free Pages/Products and Services/Downloadable Files/Back_Testing.zip)

### CTM Forecast Methodology

This paper concerns itself with the cross-sectional performance of Moody's Credit Transition Model (CTM).<sup>1</sup> For any individual issuer, CTM assigns probabilities to all future rating states, including the *default* and *withdrawal* state. An example is presented in Exhibit 3 below.

The model generates these forecasts by conditioning on certain issuer-specific features and on an expected future path of the macroeconomy. The issuer-specific features include:

- Current rating,
- Whether the issuer was upgraded or downgraded into its current rating,
- Elapsed time in the current rating,
- Elapsed time since the issuer's first rating was assigned., and
- Watchlist/outlook assignment<sup>2</sup>

The macro-economic drivers the model conditions on are two: the U.S. unemployment rate and the high yield spread over Treasuries.<sup>3</sup>

### What is Cross-Sectional Prediction?

How can we test the forecasts of CTM? Any single issuer must ultimately occupy only one rating state at a given point in the future. It will either have defaulted or not, for example. If the model assigned a 10% chance of default, but the issuer did not default, was the model "wrong?" If the model predicted that, one year from

<sup>1</sup> For a thorough discussion of Credit Transition Model, please see "A Cyclical Model Of Multiple-Horizon Credit Rating Transitions And Default," Moody's Special Comment, August 2007. A less technical discussion may be found in "Introducing Moody's Credit Transition Model," Moody's Special Comment, August 2007.

<sup>2</sup> Please see "Moody's Credit Transition Model: A Summary of the Watchlist/Outlook Extension," Moody's Special Comment, June 2008.

<sup>3</sup> Spread data are provided by Lehman's U.S. corporate high yield spread index.

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now, the issuer has a 12% chance of being rated A1, a 15% chance of A2 and an 18% chance of A3, and the issuer ultimately ends up being rated A2 – again, was the model “wrong?”

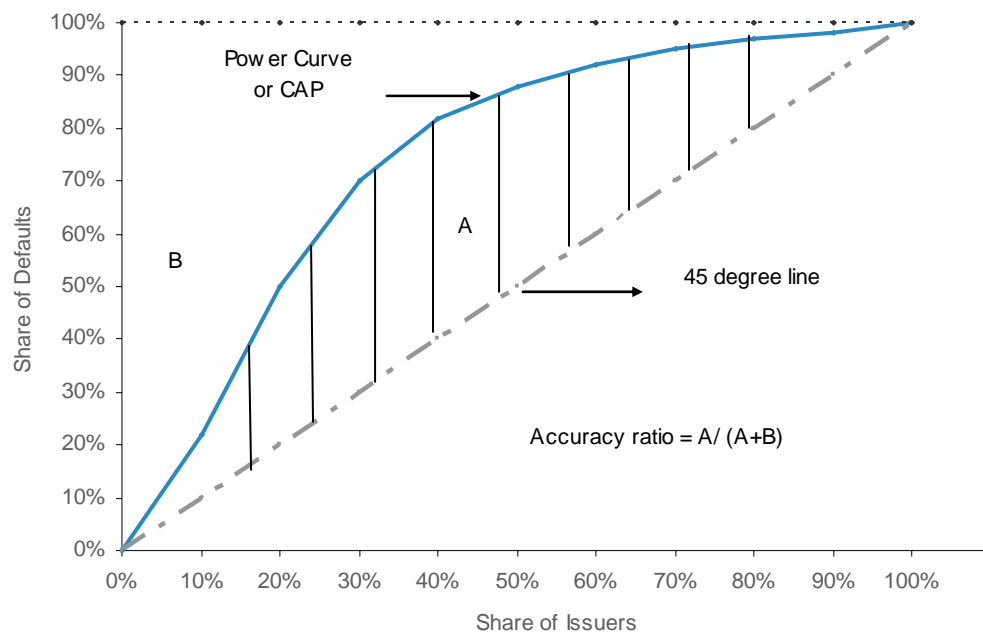
Model accuracy can only be gauged at the level of a pool of issuers, not for any individual issuer. Given a (large) set of issuers, it should be the case that those issuers which were assigned greater probabilities of default were in fact more likely to ultimately default. Since CTM predicts all manner of rating transitions, we can ask the same of its upgrade and downgrade probability forecasts: in a large pool, those probabilities should correctly order issuers in terms of their realized transitions. This cross-sectional, ordinal power of the Credit Transition Model is what we seek to test below.

### What is an Accuracy Ratio?

Moody's routinely tests the predictive power of its credit ratings. This, again, is a cross-sectional, ordinal test. The key metric used by Moody's to measure the relative accuracy of its ratings is the “cumulative accuracy profile” (or power curve) and the accuracy ratio, which is one way to compress the information in the cumulative accuracy profile into a single number.<sup>4</sup> We will use this same accuracy ratio to evaluate all the predicted transitions of CTM.

Each point along a CAP curve indicates the power of a specific rating or score as a tool to discriminate between events (e.g. defaults) and non-events (e.g. non-defaults) over a specified investment horizon, such as one quarter, one year, five years or twenty years. If we take “Default CAP Curve” as an example, it is constructed by plotting, for each score, the proportion of defaults accounted for by issuers with the same score or higher against the proportion of all issuers with the same score or higher. It is also known as a “power curve” because it shows how effective the model is at detecting defaults from the population. The curve bows toward the northwest corner, the greater the fraction of all defaults that can be accounted for by the highest default score categories. The closer the curve is to the 45° line, which is the power curve associated with randomly assigned ratings, the weaker is the information content of the model score. Exhibit 1 below illustrates the default CAP curve and accuracy ratio calculation.

**Exhibit 1: Defining CAP (Power) Curve and Accuracy Ratio (AR)**



Our back-testing reports accuracy ratios which are obtained by compressing the information on the CAP curve into a single summary statistic. The accuracy ratio is the ratio of the area between the CAP curve and the 45-

<sup>4</sup> Please see “Measuring the Performance of Corporate Bond Ratings,” Moody's Special Comment, April 2003.

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degree line (A) to the maximum possible area above the 45-degree line, which is 1/2 (B). The accuracy ratio lies between minus one and positive one. For instance, if all defaulters had the highest default probability, then the accuracy ratio would approach 1 (100%), which indicates perfect ordering. If all defaulters were distributed randomly throughout the population without regard to the default probability, the accuracy ratio would be 0. And if all defaulters were initially assigned the lowest probability of default, then the accuracy ratio would approach -1 (-100%).

For example, suppose we apply CTM to a portfolio of 10 issuers. CTM would assign 10 (generally unique) default probabilities as shown in Exhibit 2 below. In a back-testing exercise, we could check the historical record as to which of these 10 issuers actually defaulted within the forecast horizon under study. The third column contains this historical data. In this example, the accuracy ratio is 55%. If Issuer 1 actually defaulted, the AR would fall to 26%. If Issuer 10 did *not* default, the AR falls to 43%.

### Exhibit 2: Example for Accuracy Ratio Calculation

Issuer No	Probability of Default	Did it actually default?
1	0.00%	
2	0.10%	
3	0.25%	
4	1.80%	
5	2.90%	
6	3.50%	Y
7	3.60%	
8	15.8%	Y
9	29.5%	Y
10	68.5%	Y

## What is Available Online?

We have done extensive back-testing of seven transition types, namely *default*, *withdrawal*, *upgrade*, *downgrade*, *stability*, *rising star* and *fallen angel*. In this Special Comment, we will focus on some key results and generally restrict most of our discussion to the *default* transition. However, rating downgrades and upgrades can also be significant credit events, particularly for portfolios which are managed subject to credit rating investment criteria. CTM can also be used to calculate the fallen angel probability (the probability of an investment-grade issuer being downgraded to speculative-grade) and the rising star probability (the probability of a speculative-grade issuer being upgraded to investment-grade). In addition to these various transitions, CTM also has the unique ability of forecasting withdrawal probabilities.<sup>5,6</sup>

CTM provides a transition matrix for each individual issuer over time. An example is shown in Exhibit 3 below, which reports transition probabilities for a new B2 issuer over 5 years.

<sup>5</sup> For a thorough discussion of withdrawal rates and withdrawal adjusted default rates, refer to "Comparing Withdrawal Adjustment Methods: An Application of Moody's Credit Transition Model," Moody's Special Comment, March 2008.

<sup>6</sup> That we are able to predict withdrawal with some power serves as a minor rebuke to other models which are estimated under the assumption that rating withdrawal represents random censoring of the data.

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*Exhibit 3: Cumulative Transition Probabilities for a new B2 issuer*

	1q	4q	8q	12q	16q	20q
Aaa	0	0	0	0	0	0
Aa1	0	0	0	0	0	0
Aa2	0	0	0	0	0	0
Aa3	0	0	0	0	0	0
A1	0	0	0	0	0	0
A2	0	0	0	0	0	0
A3	0	0	0	0	0	0
Baa1	0	0	0	0	0	0
Baa2	0	0	0	0	0	0
Baa3	0	0	0	0	0	1
Ba1	0	0	0	1	1	1
Ba2	0	0	1	1	1	1
Ba3	0	1	2	3	3	3
B1	0	3	6	8	7	6
B2	96	80	57	36	24	16
B3	1	4	7	8	7	6
Caa1	0	2	4	5	5	4
Caa2	0	1	2	3	3	2
Caa3	0	0	1	1	1	1
Ca	0	0	1	1	1	1
C	0	0	0	0	0	0
<i>WR</i>	<i>2.8</i>	<i>6.8</i>	<i>12.0</i>	<i>19.9</i>	<i>28.2</i>	<i>36.2</i>
<i>Def</i>	<i>0.0</i>	<i>1.7</i>	<i>6.3</i>	<i>11.5</i>	<i>16.2</i>	<i>19.7</i>

*Sample output from Moody's Credit Transition Model. A new issuer rated B2 has a 96% probability of being rated B2 one quarter from now. Five years from now, there is only a 16% probability of its being rated B2, with a 19.7% probability of having defaulted and a 36.2% probability of having withdrawn.*

Since the model produces multi-horizon transition probabilities, we tested accuracy ratios for all available horizons from the 1<sup>st</sup> quarter to the 20<sup>th</sup> quarter.

The dataset we used to calculate accuracy ratios includes 40 cohorts (10 years) starting January 1<sup>st</sup>, 1998 and moving quarterly to October 1<sup>st</sup>, 2007, our last cohort. We studied 3 regions: Global, North America and Europe for all transitions. We further studied by rating categories such as investment-grade, speculative-grade and also broad rating categories. Results are further available by industry sector, defined by the Moody's 35 industries familiar to readers of our default studies. All of this information is available on [http://www.moodys.com/cust/content/Content.ashx?source=StaticContent/Free Pages/Products and Services/Downloadable Files/Back\\_Testing.zip](http://www.moodys.com/cust/content/Content.ashx?source=StaticContent/Free Pages/Products and Services/Downloadable Files/Back_Testing.zip)

### Averaging a Set of Accuracy Ratios: 4 Methods

As described above, we have, for every cut of region, industry and rating category, up to 40 cohorts to study, each of which will have its own accuracy ratio for whichever of the seven transitions is being studied at whichever of 20 horizons we are considering. This is, quite simply, an unruly amount of data to evaluate. So how shall we reduce these 40 numbers to a single number? How shall we average across accuracy ratios?

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Three methods of averaging suggest themselves:

- Equally weighted average (i.e. simple average)
- Event weighted average, and
- Non-event weighted average.

*Equally weighted average* treats each cohort equally regardless of the number of issuers or events in that cohort. Basically each cohort has the same weight in the calculation of the average accuracy ratio.

*Event weighted average* assigns a higher weight to the cohorts with higher event rates. The goal is to determine the accuracy of the model when the event rates are high (i.e., the accuracy of the model *when default rates are high*).

*Non-event weighted average* assigns a higher weight to the cohorts with lower event rates. The goal is to determine the accuracy of the model when the event rate is low (i.e., the accuracy of the model *when default rates are low*).

The accuracy ratio requires a large number of sample events in order to be meaningful. In the case of defaults, we will not (and should not) find many investment-grade events over short horizons. Consequently, the "accuracy ratio" for investment-grade ratings is not defined for short horizons, since there are no events to order. The same may be true for small industry sectors: there may simply be too few events to make the measure useful.

To create more meaningful average accuracy ratios, we filter cohorts based on the number of events in that cohort. We set a fairly loose standard, requiring a minimum of only 8 events to include a cohort in our calculations. We further check the number of cohorts which satisfy that criteria. If fewer than 8 cohorts satisfy the threshold, then we consider the accuracy ratio undefined. In short, in order to calculate an average accuracy, we must have at least 8 cohorts with at least 8 events in each.

In addition to the averaging methods mentioned above, we considered a fourth method to calculate an accuracy ratio, a *pooled method*. Rather than average across different cohorts, we simply pool all the cohorts together and calculate a single accuracy ratio. This method is useful in testing the time-series features of the model. Recall that each cohort sorts defaulters from non-defaulters with some power. But suppose the average default rate in cohort 1 is 5%, while for cohort 2 it is 10%. We would hope to find more defaulters in cohort 2 than in cohort 1. In other words, while both cohorts 1 and 2 might perfectly sort defaulters from non-defaulters, by pooling them together we see if the higher average default rate of cohort 2 was predictive of more defaulters in cohort 2.

An example may help clarify. Suppose cohorts 1 and 2 each have five issuers for which the predicted default probabilities and realized default indicators are presented in Exhibit 4 below. Individually, their accuracy ratios are 40% each. When we pool them together, we form a single cohort, as reported in Exhibit 5. The single accuracy ratio for this pooled sample is 55%.

### ***Exhibit 4: Example for Accuracy Ratio Calculation: Individual Cohorts***

Cohort/Issuer	Probability of Default	Did it actually default?
1-1	0.00%	
1-2	0.10%	
1-3	2.50%	
1-4	9.80%	Y
1-5	12.90%	
2-1	1.50%	
2-2	3.60%	
2-3	15.8%	Y
2-4	29.5%	Y
2-5	68.5%	Y

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**Exhibit 5: Example for Accuracy Ratio Calculation: Pooled Cohort**

Issuer	Probability of Default	Did it actually default?
1	0.00%	
2	0.10%	
3	1.50%	
4	2.50%	
5	3.60%	
6	9.80%	Y
7	12.90%	
8	15.80%	Y
9	29.50%	Y
10	68.50%	Y

### Results: Accuracy Ratios by Averaging Method

Exhibit 6 shows the *default* accuracy ratios calculated for the January 1998 cohort over the subsequent 20 quarters. As can be seen, the model's accuracy is 92.70% for the first quarter, decreasing at longer forecast horizons. While this decrease is to be expected (forecast accuracy generally declines with horizon), CTM still has a high accuracy ratio - 72.1% - even in the 20<sup>th</sup> quarter.

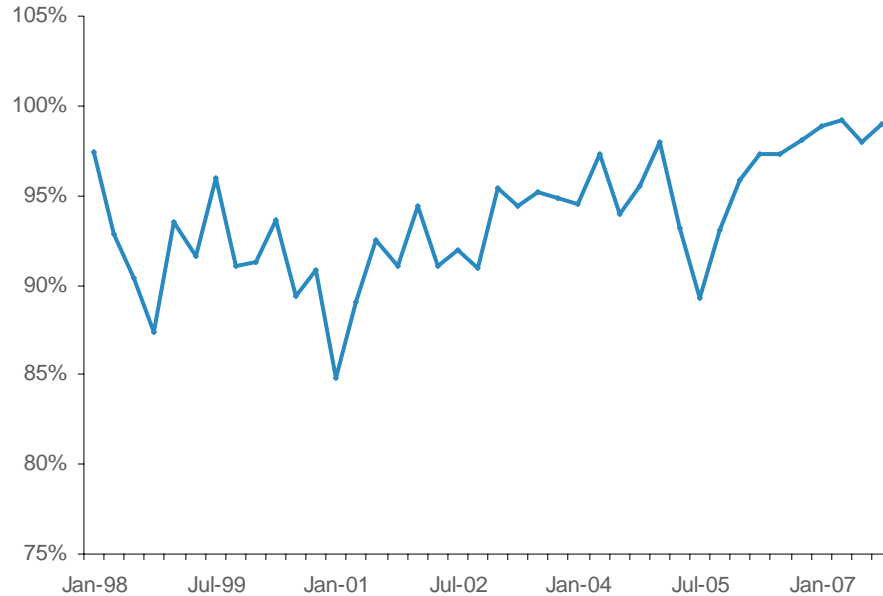
**Exhibit 6: Global Default Accuracy Rate by Horizon: January 1998 Cohort**

Horizon	Accuracy Ratio
1	92.70%
2	90.97%
3	88.31%
4	86.16%
5	84.42%
6	83.07%
7	81.93%
8	80.81%
9	79.74%
10	78.82%
11	77.96%
12	77.19%
13	76.46%
14	75.84%
15	75.26%
16	74.64%
17	73.97%
18	73.36%
19	72.69%
20	72.07%

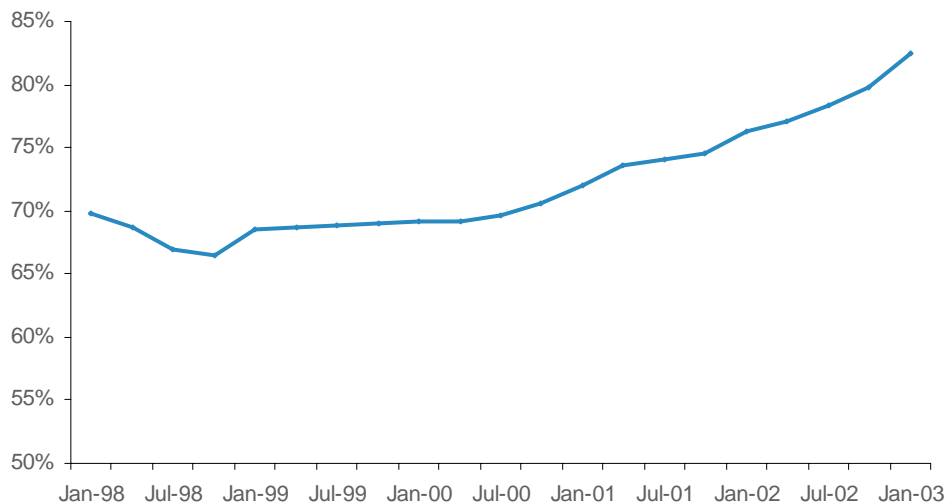
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The same pattern holds for other cohorts. Exhibit 7 shows the 1<sup>st</sup> quarter *default* accuracy ratio for all cohorts, and Exhibit 8 shows the 20<sup>th</sup> quarter accuracy ratio. Both 1<sup>st</sup> quarter and especially 20<sup>th</sup> quarter accuracy ratios seem to be increasing for the later cohorts.

**Exhibit 7: 1<sup>st</sup> Quarter Default Rate Accuracy for Global Cohorts**



**Exhibit 8: 20<sup>th</sup> Quarter Default Rate Accuracy for Global Cohorts**



We wish to compress these cohort time-series data into single performance metrics by averaging in the different ways explained above. Exhibit 9 shows the results. Considering first quarter accuracy – the time-series of which was plotted above – the pooled AR is 93.01%, while the simple average of all 40 cohorts is 92.70%. This is identical to the non-default-rate weighted average of 92.71%, which is better than the default-rate weighted average AR of 91.94%. Taken together, we might conclude that over the first quarter forecast horizon, CTM is somewhat more accurate in low default states than in high. Furthermore, its time-series power is evident in the higher pooled AR: those quarters with a higher predicted default rate actually had more defaults, as should be the case.

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### Exhibit 9: Global Default Accuracy Ratios

Quarters	Pooled	Simple Average	Non-Event Weighted	Event Weighted
1	93.01%	92.70%	92.71%	91.94%
4	86.23%	86.16%	86.21%	83.17%
8	81.31%	80.81%	80.93%	77.50%
12	78.02%	77.19%	77.34%	74.43%
16	75.14%	74.64%	74.79%	72.43%
20	72.22%	72.07%	72.18%	70.83%

Exhibit 10 shows the *downgrade* accuracy ratios for Global issuers over different forecast horizons. We notice first of all that the accuracy ratios are lower for *downgrade* than they are for *default*. This should not surprise us. CTM is based on credit ratings, and credit ratings are designed to order default risk; they are not designed to order downgrade risk.<sup>7</sup> Nevertheless, the results of Exhibit 10 are qualitatively similar to Exhibit 9. Forecast accuracy declines with horizon. The pooled AR is almost always greater than any of the other averages, indicating the time-series power of CTM again. The non-event-weighted average is greater than the event-weighted, suggesting that CTM is better able to order downgraders in stable environments.

### Exhibit 10: Downgrade Accuracy Ratios

Quarters	Pooled	Simple Average	Non-Event Weighted	Event Weighted
1	68.48%	67.28%	67.34%	65.76%
4	42.79%	41.97%	42.30%	39.27%
8	32.29%	30.87%	31.21%	29.18%
12	28.58%	27.12%	27.33%	26.31%
16	28.18%	27.44%	27.53%	27.10%
20	29.33%	29.41%	29.48%	29.17%

Exhibit 11 shows the *upgrade* accuracy ratios for Global issuers over time. The results are similar to *downgrade* in magnitude. The time-series power of CTM is once again in evidence. Interestingly, the model appears equally effective in high- and low-upgrade environments.

### Exhibit 11: Upgrade Accuracy Ratios

Quarters	Pooled	Simple Average	Non-Event Weighted	Event Weighted
1	68.59%	66.65%	66.61%	68.34%
4	49.27%	47.48%	47.38%	48.53%
8	38.05%	36.35%	36.29%	36.80%
12	32.62%	30.82%	30.81%	30.91%
16	29.78%	28.98%	29.00%	28.88%
20	28.37%	28.71%	28.70%	28.77%

Exhibit 12 shows the *stability* accuracy ratios for Global issuers. By stability we mean unchanged rating. What is most striking about Exhibit 12 is that model accuracy is increasing in forecast horizon from 4.53% in the 1<sup>st</sup> quarter to 31.05% in the 20<sup>th</sup> quarter. It becomes easier to predict stable issuers in later quarters as the sample size actually decreases due to exit to *default* and *withdrawal*. In other words, it would appear that CTM is able to distinguish those who will exit the sample from those who will not, and thus, somewhat

<sup>7</sup> While we would say that an A2 issuer is at less risk of *default* than a B2 issuer, we would not generally say that it is at less risk of *downgrade* or *upgrade*.

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indirectly, those whose rating will remain unchanged from those whose rating will change. There is some indication of time-series power, but it is less pronounced than with the other transitions we have studied.

### *Exhibit 12: Stability Accuracy Ratio*

Quarters	Pooled	Simple Average	Non-Event Weighted	Event Weighted
1	4.53%	4.53%	4.68%	4.52%
4	11.92%	11.71%	11.73%	11.71%
8	18.53%	18.20%	18.17%	18.23%
12	23.18%	22.92%	22.91%	22.94%
16	27.53%	27.26%	27.25%	27.30%
20	31.05%	30.76%	30.76%	30.78%

Exhibit 13 shows the *withdrawal* accuracy ratios for Global issuers over various forecast horizons. This is a unique output of the model and critical for portfolio managers. The pooled AR's are again greater than the other averages, suggesting a significant time-series power of CTM. The model appears equally effective in high- and low-withdrawal environments.

### *Exhibit 13: Withdrawal Accuracy Ratio*

Quarters	Pooled	Simple Average	Non-Event Weighted	Event Weighted
1	35.44%	34.28%	34.27%	34.43%
4	31.29%	30.18%	30.18%	30.24%
8	27.54%	26.41%	26.39%	26.49%
12	24.36%	23.36%	23.33%	23.47%
16	21.86%	20.98%	20.93%	21.11%
20	19.33%	18.70%	18.67%	18.77%

Exhibit 14 shows the *fallen angel* accuracy ratios for Global issuers over time. CTM's performance is again very strong, with a pooled AR of 91.2% in the first quarter and 57.1% in the 20<sup>th</sup> quarter. The time-series power is somewhat more muted, and it would appear the model's power is greater in more stable environments.

### *Exhibit 14: Fallen Angel Accuracy Ratio*

Quarters	Pooled	Simple Average	Non-Event Weighted	Event Weighted
1	91.20%	91.20%	91.21%	89.66%
4	80.14%	80.00%	80.04%	77.59%
8	70.91%	71.21%	71.29%	69.05%
12	64.00%	63.72%	63.78%	62.51%
16	60.02%	59.59%	59.64%	58.84%
20	57.05%	56.79%	56.83%	56.20%

Similarly, Exhibit 15 shows the *rising star* accuracy ratios. CTM would appear quite powerful in this dimension as well. Model performance is more balanced between high- and low-event environments.

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### Exhibit 15: Rising Star Accuracy Ratio

Quarters	Pooled	Simple Average	Non-Event Weighted	Event Weighted
1	90.62%	90.97%	90.97%	90.79%
4	79.65%	81.27%	81.29%	80.57%
8	73.42%	74.95%	74.97%	74.29%
12	70.64%	71.22%	71.27%	70.43%
16	68.86%	69.04%	69.08%	68.25%
20	69.62%	70.01%	70.01%	70.06%

## Results: Accuracy Ratios by Region

In this section we present regional accuracy ratios for all transitions. We studied three regions: Global, North America and Europe. Additional results, not presented below, are available at [http://www.moodys.com/cust/content/Content.ashx?source=StaticContent/Free Pages/Products and Services/Downloadable Files/Back\\_Testing.zip](http://www.moodys.com/cust/content/Content.ashx?source=StaticContent/Free Pages/Products and Services/Downloadable Files/Back_Testing.zip).

Exhibits 16 through 22 present accuracy ratios for various transition risks as indicated summarized by their simple average. The exhibits distinguish the three regions from each other. The Global results are repeated from the above exhibits. For almost all transitions, including the all important *default* transition, the model has exhibited greater cross-sectional power in Europe. This is especially noteworthy since the European portfolio was not part of the model estimation sample.

### Exhibit 16: Regional Default Accuracy Ratios, Simple Averages

Quarters	Global	North America	Europe
1	92.70%	90.32%	NA
4	86.16%	83.48%	89.39%
8	80.81%	77.17%	88.05%
12	77.19%	72.85%	86.78%
16	74.64%	70.07%	86.42%
20	72.07%	67.54%	84.36%

### Exhibit 17: Regional Downgrade Accuracy Ratios, Simple Averages

Quarters	Global	North America	Europe
1	67.28%	63.35%	72.07%
4	41.97%	39.06%	44.68%
8	30.87%	28.63%	34.32%
12	27.12%	26.30%	30.88%
16	27.44%	27.62%	29.49%
20	29.41%	29.72%	29.56%

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**Exhibit 18: Regional Upgrade Accuracy Ratios, Simple Average**

Quarters	Global	North America	Europe
1	66.65%	65.98%	69.04%
4	47.48%	48.57%	53.71%
8	36.35%	37.39%	44.18%
12	30.82%	31.77%	39.22%
16	28.98%	29.34%	37.15%
20	28.71%	28.56%	36.52%

**Exhibit 19: Regional Stability Accuracy Ratios, Simple Average**

Quarters	Global	North America	Europe
1	4.53%	4.37%	4.27%
4	11.71%	11.41%	11.11%
8	18.20%	17.22%	17.53%
12	22.92%	21.93%	22.71%
16	27.26%	26.18%	26.49%
20	30.76%	29.43%	29.78%

**Exhibit 20: Regional Withdrawal Accuracy Ratios, Simple Average**

Quarters	Global	North America	Europe
1	34.28%	35.60%	34.31%
4	30.18%	30.49%	31.26%
8	26.41%	26.21%	27.88%
12	23.36%	23.26%	24.18%
16	20.98%	20.92%	21.60%
20	18.70%	18.76%	18.72%

**Exhibit 21: Regional Fallen Angel Accuracy Ratios, Simple Average**

Quarters	Global	North America	Europe
1	91.20%	88.45%	NA
4	80.00%	76.59%	81.50%
8	71.21%	67.35%	76.24%
12	63.72%	60.39%	67.35%
16	59.59%	56.39%	61.48%
20	56.79%	53.77%	57.94%

## Testing The Cross-Sectional Power Of The Credit Transition Model

**Exhibit 22: Regional Rising Star Accuracy Ratios, Simple Average**

Quarters	Global	North America	Europe
1	90.97%	89.27%	NA
4	81.27%	82.06%	79.07%
8	74.95%	75.49%	77.46%
12	71.22%	72.56%	66.97%
16	69.04%	71.23%	64.29%
20	70.01%	73.20%	61.02%

### Results: Accuracy Ratios by Rating Category

We also test CTM's cross-sectional power by rating categories. These can be more stringent tests, since ratings are intended to order some transition risks and we are, by construction, losing that information. We don't need CTM in order to know that a Aaa credit is at lower risk of default than a B credit. But what about one B credit versus another? Is CTM able to distinguish default (and other risks) at this level?

Exhibit 23 shows the default accuracy ratios for investment-grade, speculative-grade and by broad rating categories. These ratios are for the Global region and represent simple averages across cohorts. Readers can find more detailed breakdowns online at

[http://www.moodys.com/cust/content/Content.ashx?source=StaticContent/Free Pages/Products and Services/Downloadable Files/Back\\_Testing.zip](http://www.moodys.com/cust/content/Content.ashx?source=StaticContent/Free Pages/Products and Services/Downloadable Files/Back_Testing.zip).

Not surprisingly, within rating categories CTM has less cross-sectional power than it has across rating categories when it comes to identifying defaulters. However, it still has substantial power. In other words, given the more difficult task of sorting defaulters from non-defaulters for issuers with the same rating, CTM remains effective.

**Exhibit 23: Default Accuracy Ratios for Investment- and Speculative-Grade Issuers and Broad Rating Categories**

Quarters	Investment Grade	Speculative Grade	Broad Rating Categories					
			Aaa-Aa	A	Baa	Ba	B	Caa-C
1	NA	82.37%	NA	NA	NA	NA	56.21%	60.14%
4	NA	68.17%	NA	NA	NA	54.41%	44.05%	48.30%
8	60.01%	56.42%	NA	NA	23.32%	41.55%	36.33%	32.79%
12	65.83%	49.18%	NA	NA	33.14%	36.41%	29.48%	22.65%
16	64.73%	44.50%	NA	NA	30.52%	33.81%	24.70%	18.02%
20	64.65%	40.40%	NA	NA	31.41%	31.08%	21.57%	17.31%

### Results: Accuracy Ratios by Industry

We also study CTM's performance within Moody's 35 industries by different regions. Exhibits 24(a) and 24(b) present just some of the results available, showing default accuracy by select Moody's 35 industries for Global issuers. A complete list of Moody's 35 industries can be found in the Appendix. CTM continues to do well discriminating defaulters from non-defaulters within each industry. Users can find the results on other transitions, regions and industries online at

[http://www.moodys.com/cust/content/Content.ashx?source=StaticContent/Free Pages/Products and Services/Downloadable Files/Back\\_Testing.zip](http://www.moodys.com/cust/content/Content.ashx?source=StaticContent/Free Pages/Products and Services/Downloadable Files/Back_Testing.zip).

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**Exhibit 24(a): Default Accuracy Ratios by Industry**

Quarters	Automotive	Capital equipment	Consumer Goods	Hotel, Gaming & Leisure
1	NA	NA	NA	NA
4	NA	72.24%	66.25%	NA
8	72.53%	70.04%	58.96%	54.16%
12	67.11%	66.47%	55.24%	54.59%
16	66.87%	68.58%	55.06%	56.01%
20	66.77%	65.12%	53.74%	56.74%

**Exhibit 24(b): Default Accuracy Ratios by Industry, continued**

Quarters	Metals & Mining	Retail	Telecommunications	Wholesale
1	NA	NA	NA	NA
4	76.99%	73.18%	72.07%	NA
8	69.29%	65.73%	67.32%	57.92%
12	62.69%	66.30%	64.36%	53.91%
16	60.43%	66.82%	62.09%	53.01%
20	59.96%	66.70%	58.28%	52.72%

## Conclusion

We have performed extensive back-testing of the Credit Transition Model's ability to sort issuers by a variety of transition risks, namely *default*, *withdrawal*, *upgrade*, *downgrade*, *stability*, *rising star* and *fallen angel*. We studied each transition risk by region, industry, initial rating category, and forecast horizon. We further considered performance on average, pooled across time, in high-risk environments and in low-risk environments.

In this paper we have defined some key concepts and presented just some of the model back-testing results. The full set of results is available at

[http://www.moodys.com/cust/content/Content.ashx?source=StaticContent/Free Pages/Products and Services/Downloadable Files/Back\\_Testing.zip](http://www.moodys.com/cust/content/Content.ashx?source=StaticContent/Free Pages/Products and Services/Downloadable Files/Back_Testing.zip)

## Testing The Cross-Sectional Power Of The Credit Transition Model

### Appendix: Moody's 35 Industries

1	Aerospace & Defense
2	Automotive
3	Banking
4	Beverage, Food, & Tobacco
5	Capital Equipment
6	Chemicals, Plastics, & Rubber
7	Construction & Building
8	Consumer goods: durable
9	Consumer goods: non-durable
10	Containers, Packaging, & Glass
11	Energy: Electricity
12	Energy: Oil & Gas
13	Environmental Industries
14	FIRE: Finance
15	FIRE: Insurance
16	FIRE: Real Estate
17	Forest Products & Paper
18	Healthcare & Pharmaceuticals
19	High Tech Industries
20	Hotel, Gaming, & Leisure
21	Media: Advertising, Printing & Publishing
22	Media: Broadcasting & Subscription
23	Media: Diversified & Production
24	Metals & Mining
25	Retail
26	Services: Business
27	Services: Consumer
28	Sovereign & Public Finance
29	Telecommunications
30	Transportation: Cargo
31	Transportation: Consumer
32	Utilities: Electric
33	Utilities: Oil & Gas
34	Utilities: Water
35	Wholesale

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### Author(s)

Albert Metz

### Production Specialist

Cassina Brooks

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