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Special Comment

Moody's
Credit Policy

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Introducing Moody's Credit Transition Model

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Analyst Contacts:

New York 1.212.553.1653

Albert Metz
Senior Credit Officer

Richard Cantor
Team Managing Director

Summary

Moody's new Credit Transition Model forecasts probabilities of default, upgrade and downgrade conditional on the future path of the economy for arbitrary portfolios of issuers over variable time horizons. Several new exhibits based on this model will be included in future versions of Moody's Monthly Default Report. This Special Comment introduces those exhibits, the model, and several of its applications, including:

- Forecasting default probabilities for a single issuer or any portfolio of issuers.
- Forecasting complete rating transition probabilities, including to the default and *withdrawal* state, for any portfolio of issuers.
- Performing scenario analysis with respect to different economic forecasts: how will a portfolio of credits behave in a recession, expansion, or a stable economy?
- Generating transition probabilities – including default probabilities – on either an issuer- or volume-weighted basis.
- Calculating probabilities of first passage across a given rating threshold. This would be useful for any portfolio governed by strict credit rating investment criteria (e.g., a portfolio which can only hold investment-grade debt). Such forecasts, to our knowledge, are not available from any other source.
- Performing portfolio risk analysis: given a probability of default for each issuer (or the average for a pool), what is the distribution of expected losses?

The model conditions on various rating factors, such as an issuer's current rating, how long it has maintained that rating, how long it has maintained any rating, and whether the issuer was upgraded or downgraded into its current rating. Other conditioning information includes the future path of two economic drivers: the U.S. unemployment rate, and the spread of high yield credits over Treasuries. The model itself is of the discrete time, multiple-destination proportional hazard type. For a technical discussion of the model, please refer to Moody's August 2007 Special Comment "A Cyclical Model of Multiple-Horizon Credit Rating Transitions and Default."

Moody's Investors Service

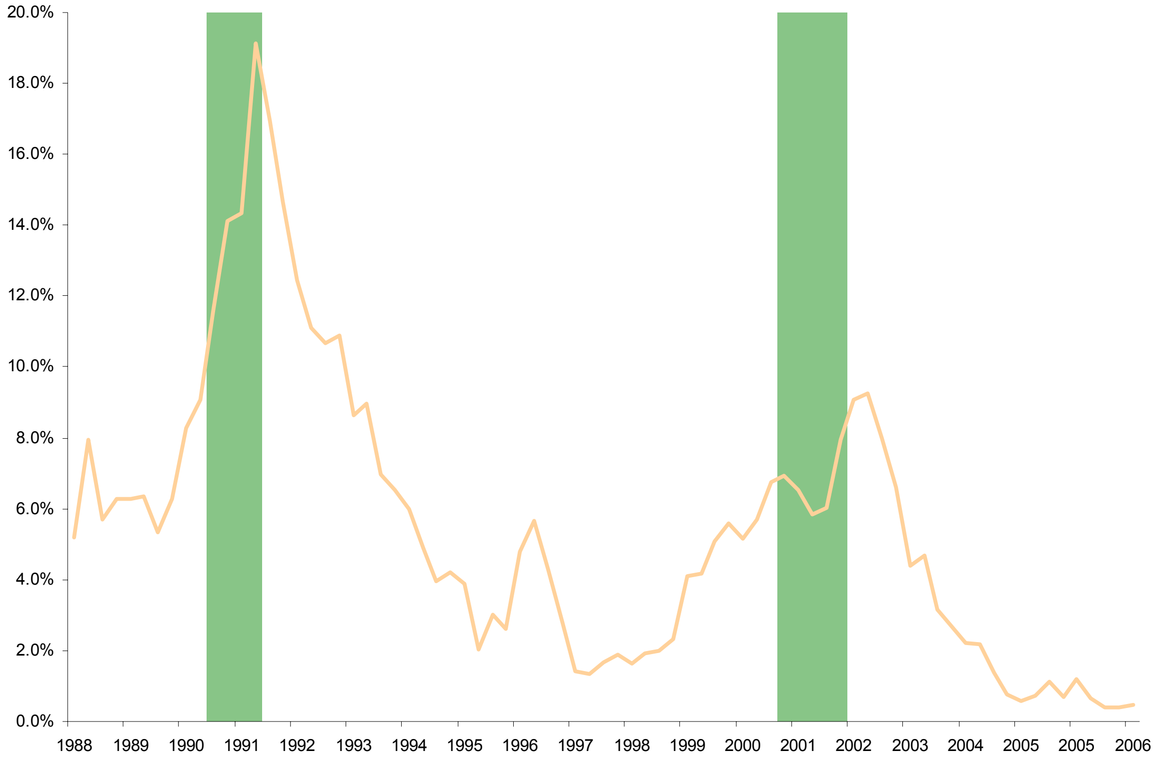
Introducing Moody's Credit Transition Model

I Introduction

Credit ratings are intended as relative assessments of expected loss. They are not intended to capture a *particular* default probability over a *particular* horizon. Simple inspection of the data indicates that within a rating category, default rates rise and fall over time, and sometimes quite significantly. Furthermore, their cycle – again, conditional on rating – is strongly correlated with the economic cycle. Figure 1 shows the one year default rate for B rated issuers since 1987. The variance, and the correlation with U.S. recessions, is apparent.

As ordinal measures of relative credit risk, ratings have proven themselves effective.[1] The problem we want to solve is, how can we take the ordinal content of credit ratings and translate them into particular, cardinal default probabilities? What is the "one year default probability" of a B2 rating, and how will that change as the economic cycle changes?

Figure 1: Single-B One Year Default Rates



In some cases, default is not the only credit event of interest. Upgrades and downgrades, particular from investment- to speculative-grade, can be important. Common practice is to assemble average transition probabilities in a matrix, as shown in Tables 1 and 2 below, and use them as forecasts. But this ignores that first, rating transitions exhibit momentum (downgrades are more likely followed by downgrades than upgrades), and second, credit transitions are also correlated with the economic cycle.

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[1] *See for example, "The Performance of Moody's Corporate Bond Ratings: March 2007 Quarterly Update," Moody's Special Comment, April 2007.*

Introducing Moody's Credit Transition Model

Table 1: One Year Transition Matrix (Percent)

Current Rating	One Year Later																					
	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3	Caa1	Caa2	Caa3	Ca-C	WR	DEF
Aaa	**89**	3	3	0		0															5	
Aa1	3	**82**	5	5	0	0	0	0													5	
Aa2	1	3	**79**	8	2	1	0		0	0											7	
Aa3	0	1	3	**79**	7	2	1	0	0		0			0							6	
A1	0	0	0	5	**80**	7	2	1	0	0	0	0	0								5	
A2	0	0	0	1	5	**79**	7	3	1	0	0	0	0		0			0	0		4	0
A3	0	0	0	0	1	8	**74**	7	3	1	0	0	0	0	0	0		0	0	0	4	0
Baa1	0	0	0	0	0	2	6	**75**	8	3	1	0	0	0	0	0	0	0		0	4	0
Baa2	0	0	0	0	0	1	2	6	**76**	7	1	1	1	1	0	0	0	0	0	0	5	0
Baa3	0	0		0	0	0	1	2	8	**73**	5	3	1	1	0	0	0	0	0	0	5	0
Ba1			0	0	0	0	0	1	2	9	**65**	5	4	1	1	1	0	0	0	0	8	0
Ba2			0	0	0	0	0	0	1	3	8	**63**	6	4	2	1	1	0	0	0	9	1
Ba3			0	0	0	0	0	0	0	1	3	7	**65**	5	5	2	0	0	0	0	10	2
B1	0	0		0	0	0	0	0	0	0	1	2	6	**66**	6	4	1	1	0	0	9	3
B2	0		0	0	0	0	0	0	0	0	0	0	2	5	**67**	7	3	1	1	0	9	4
B3		0	0		0		0	0		0	0	0	0	2	5	**61**	5	4	1	1	11	9
Caa1						0				0		0	0	1	2	5	**59**	5	4	3	11	10
Caa2						0			0	0	0	0	0	1	1	2	3	**54**	3	4	13	18
Caa3											0		0	1	1	2	3	3	**45**	6	13	25
Ca-C														0		0	1	1	1	**35**	13	20

Table 2: Five Year Transition Matrix (Percent)

Current Rating	Five Years Later																					
	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3	Caa1	Caa2	Caa3	Ca-C	WR	DEF
Aaa	**56**	7	10	3	1	1	0		0	0	0										20	
Aa1	9	**46**	10	9	3	3	1	2	1	0			0								17	
Aa2	4	6	**32**	16	5	6	3	2	0	0	0	0									26	
Aa3	1	4	8	**35**	16	9	4	2	1	0			0	0							20	
A1	1	2	3	9	**33**	15	8	4	2	1	1	1	0	0		0		0			20	0
A2	0	1	1	3	11	**34**	14	8	4	2	1	1	1	0	0	0	0			0	20	0
A3	0	0	0	2	4	19	**24**	13	8	5	2	2	1	1	0	0	0	0		0	17	1
Baa1	1	1	0	1	2	6	12	**29**	13	7	2	2	1	1	0	0	0	0	0	0	19	1
Baa2	0	0	0	1	1	3	6	11	**31**	13	3	2	2	2	1	1	1	0	0	0	20	1
Baa3	1	0	0	0	1	2	3	6	15	**26**	7	4	4	2	2	1	1	0	0	0	23	3
Ba1	0	0	0	0	1	2	3	3	7	11	**18**	5	4	5	4	1	1	0	0	0	31	4
Ba2		0		0	0	0	1	2	3	8	9	**13**	7	7	5	2	1	0	0	0	36	5
Ba3	0		0	0	0	0	1	1	2	3	4	6	**13**	7	6	3	1	1	0	1	39	11
B1	0	0	0	0	0	0	0	0	0	2	2	3	6	**13**	7	5	2	1	1	1	39	17
B2	0			0		0	0	0	0	0	1	1	2	6	**15**	8	4	2	1	1	35	23
B3						0	0	0	0	0	0	1	1	4	4	**10**	3	2	1	1	38	32
Caa1									0	0	1	1	1	3	3	4	**8**	3	1	1	36	39
Caa2								0	0	0	0	1	1	2	1	2	2	**5**	1	3	41	40
Caa3											1	1		1	1		1	0	**2**	0	31	62
Ca-C											0			0	2	2	1	1	1	**4**	43	46

Moody's Credit Transition Model couples credit ratings with the economic cycle. It allows us to assign an expected default rate to a rated credit, and to any portfolio of rated credits, conditional on the path of the macroeconomy. It actually generates complete transition forecasts for credits. Furthermore, these forecasts can be extended over any horizon, from one quarter to five years (or more).

Using this model, a portfolio manager can forecast the expected default rate over the next three years for several different portfolios, or the probability of some issuers becoming fallen angels over the next 18 months, all conditional on different economic scenarios. These forecasts are internally consistent as we aggregate different sets of credits or examine different horizons. It is one model, not a series of disconnected models.

When a portfolio is subject to strict credit rating investment criteria, a risk manager must determine the probability of a rating crossing a given threshold and when that transition might occur. For example, a credit might currently be rated Baa2, and we need the probability that within two years it will have fallen below Baa3. A typical transition matrix does not provide such first-passage probabilities. A two year transition matrix may tell us the probability that, two years from now, the credit will be spec-grade. But there is some probability that the rating would fall below Baa3 but then reverse, and while that probability might be "small," it may be important to a risk manager – especially if several credits have correlated transition paths. Far more importantly, published transition matrices generally include a *withdrawn* state, but provide no information as to what share of withdrawn issuers had first transitioned below Baa3, for example. To use a transition matrix such as Table 2 to conclude that a Baa2 issuer has a 12% probability of becoming spec-grade over the next five years grossly underestimates the actual probability of approximately 18%.

Even in cases where the cumulative downgrade probability and the cumulative first-passage probability are essentially the same (since reversals are rare, especially over short horizons), a risk manager may need to know the transition probability at each particular date. While there might be a 10% chance of the credit becoming spec-grade over two years, what may be of interest is the probability of becoming spec-grade *in* the first quarter from now versus the second versus the third and so on. In short, marginal transition probabilities might be required. These can only be crudely approximated by chaining together or differencing various transition matrices, but the Credit Transition Model delivers them quite naturally.

This Special Comment is intended to serve as an introduction to this new model; a complete technical discussion is available in Moody's August 2007 Special Comment "A Cyclical Model of Multiple-Horizon Credit Rating Transitions and Default." Below we will present examples of some model output. Many of these examples will become regular exhibits in Moody's Monthly Default Report. Section II compares this new model with other classes of models, including the one-year SG default model Moody's currently uses in its Monthly Default Report. The economic forecasts which underlie the results of this report are presented in Section III. These forecasts are illustrative – the do not represent Moody's actual opinion of the future path of these economic series. Section IV presents exhibits from the new model devoted to default forecasts, while Section V focuses on general rating transitions, including a comparison of cumulative transition probabilities with "first-passage" probabilities. Section VI briefly considers portfolio risk analysis using outputs from the new model, while Section VII concludes.

II Comparing Models

Default models, or more generally any transition model, span a variety of technologies but are essentially of two basic types: issuer-based or aggregate time-series. Time-series models, such as the one Moody's historically presented in its Monthly Default Report, exploit the correlation between default rates and the macroeconomy by regressing the former on indicators of the latter.[2] Since this correlation is strong, and probably fairly stable, they often perform quite well for the sample on which they are estimated. Indeed, the only objective of the model is to "maximize fit" between the average default rate on the one hand and the state of the economy on the other.

But their success in this one objective highlights their limitations: they cannot be applied to other portfolios (let alone a single credit), and they only provide a transition probability for a given horizon. We might say that they are both portfolio- and horizon-dependent. A "one year spec-grade default model" cannot be used to provide a "five year spec-grade default rate" or a "one year Automotive Industry default rate" or a "one year single B-rating category default rate." Each additional application requires a separate model, and unless great care is taken, nothing guarantees that these different models will yield mutually consistent forecasts.

Issuer-based models, whether of Altman's discriminant analysis type, or more common Logit or Probit models, attempt to explain *which* issuers from a given set are more likely to default over a given horizon. As such, they may be used to provide a transition probability for any arbitrary aggregation of issuers, and hence they avoid the portfolio-dependence inherent to time-series models.[3] But they do not avoid the horizon-dependence. It remains true that if one seeks a five year default rate, one needs a five year model. And, just as with time-series models, nothing guarantees mutually consistent forecasts as one chains together separate models.

While the portfolio flexibility of issuer models is advantageous, it comes at a cost. The model is no longer exclusively trying to get the average default rate "right." It is really trying to discriminate between which issuers default and which don't. Issuer-specific data (whether financial ratios, market variables or credit ratings) will largely solve this problem: "strong" issuers don't default, "weak" ones do – what role is there for the economy? The answer is, the macroeconomy will explain why similarly "weak" credits default *some* times and not others. This may be an important part of the story, but much of the observed correlation between the average default rate and the economic cycle will be obscured in an issuer-based model because the economic cycle *causes* weak financial ratios, for example. One might even imagine (though probably never see in practice) that after conditioning fully on an issuer's financial health including its future prospects, there is no residual role left for the macroeconomic drivers. Imagine that interest coverage explains default, and imagine that the economy drives interest coverage. In the aggregate time-series data, we would observe a strong correlation between default and the economy. But in an issuer model, after conditioning on issuers' interest coverage, the state of the economy would have no additional explanatory power – and thus would appear "insignificant."[4]

For a user interested only in getting the average default rate "right" for a given universe of credits over a given horizon, it is quite likely that the appropriate time-series model would be the most effective. Heuristically, this model is not wasting any information on solving the tangential problem (to this user) of figuring out which issuers default and which don't. It would seem unlikely that any issuer model would outperform a time-series model on this particular task. The advantages of the issuer model are that it can perform other tasks as well – it can be applied to other portfolios in a mutually consistent way. We must decide which is more valuable: portfolio flexibility, or point-in-time accuracy. But whatever we decide, we are left with horizon-dependence.

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[2] *Such indicators may of course include summary measures of the ratings distribution, as is the case with Moody's current model. For a detailed discussion of that model, please see "Predicting Default Rates: A Forecasting Model for Moody's Issuer-Based Default Rates," Moody's Special Comment, August 1999.*

[3] *Portfolio aggregations exploit the conditional independence assumption required for estimating these models. That is the assumption that conditional on the facts of the model (e.g., credit rating, or financial ratios, or the state of the economy), defaults are independent events. It does not assume that two firms cannot be expected to default more or less at the same time – indeed, to the extent that defaults are driven by the state of the economy which is common to all issuers, observed defaults will be correlated. It assumes that a default by firm A will not cause a default by firm B. This assumption may not hold in certain parent/sub situations, for instance.*

[4] *There would be nothing wrong with this result, but it reminds us to use caution when interpreting the impact of macroeconomic drivers in an issuer model.*

And whatever we decide, we still require different models for different transition types: upgrade, downgrade and default.

Moody's new Credit Transition Model is an issuer-based model, but as an application of the proportional-hazards model, it is not horizon-dependent. It is a single model which forecasts all transitions, it may be applied over any horizon of interest, and like all issuer models, it may be aggregated up to any portfolio of credits.

There is another very significant difference between the new model and most other transition models, a difference which may appear advantageous or disadvantageous to different users. That is that the model conditions on a future path of the economic drivers, rather than just on the currently observed economic state.[5] To use the model, one must have a forecast of the U.S. unemployment rate and high yield spread over Treasuries.[6] This is costly – it requires an auxiliary forecast – but it represents a further degree of flexibility. Risk managers can run their portfolios through different economic scenarios, and choose as a benchmark whatever scenario they feel is most plausible. We can obtain a distribution of expected transition rates as a function of the distribution of future economic paths.

Moody's Credit Transition Model is therefore an extremely flexible model: it may be applied to any portfolio, over any horizon, to explore any type of rating transition, subject to different economic scenarios. Does all of this flexibility come at the cost of accuracy? Just how good are these predictions?

The accuracy of the model's forecasts will depend on the accuracy of the economic forecasts that go into it. So the question becomes, if we have a good, even perfect, economic forecast, how well does the model predict rating transitions conditional thereon? Figures 2-5 compare the model prediction with realized transitions for default, upgrades, downgrades and net rating drift all over five year horizons. These are applied to the global rated universe and assume perfect foresight of the U.S. unemployment rate and high yield spreads. We see in all cases a very close correspondence between actual and predicted transitions. The flexibility of the Credit Transition Model would not appear to have cost us much accuracy.

Are these figures merely an in-sample fit? To some extent, yes. Even though these figures are applied to the global rated universe, the model was estimated only on the North American rated universe – but that certainly represents the largest share of issuers. So we must concede that most of the issuers were part of the estimation sample. But these are five year transitions. To calculate a five year default probability for an issuer, we must calculate the probability that over the first quarter it directly defaults, that it is upgraded to one of several ratings, that it is downgraded to one of several ratings, that it withdraws and (as a residual) that it remains unchanged. From each of these new ratings, we must make a similar set of calculations for the second quarter. And so on. All in all, for a 20 quarter forecast, we must calculate approximately 8,400 transitions for each issuer. A good analogy is to imagine using a set of data to estimate the parameters of a VAR, and then going back in time to apply the VAR sequentially to generate long-horizon forecasts. The results are certainly not "out-of-sample," but neither are they trivially in-sample, as is the case when comparing a fit line in a regression, for example.

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[5] The rating facts which the models conditions on are all currently observed.

[6] In future editions of the Monthly Default Report these forecasts will be provided by Moody's Economy.Com.

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Figure 2: Five Year Cumulative Default Rate and Model Forecast

Figure 3: Five Year Cumulative Upgrade Rate and Model Forecast

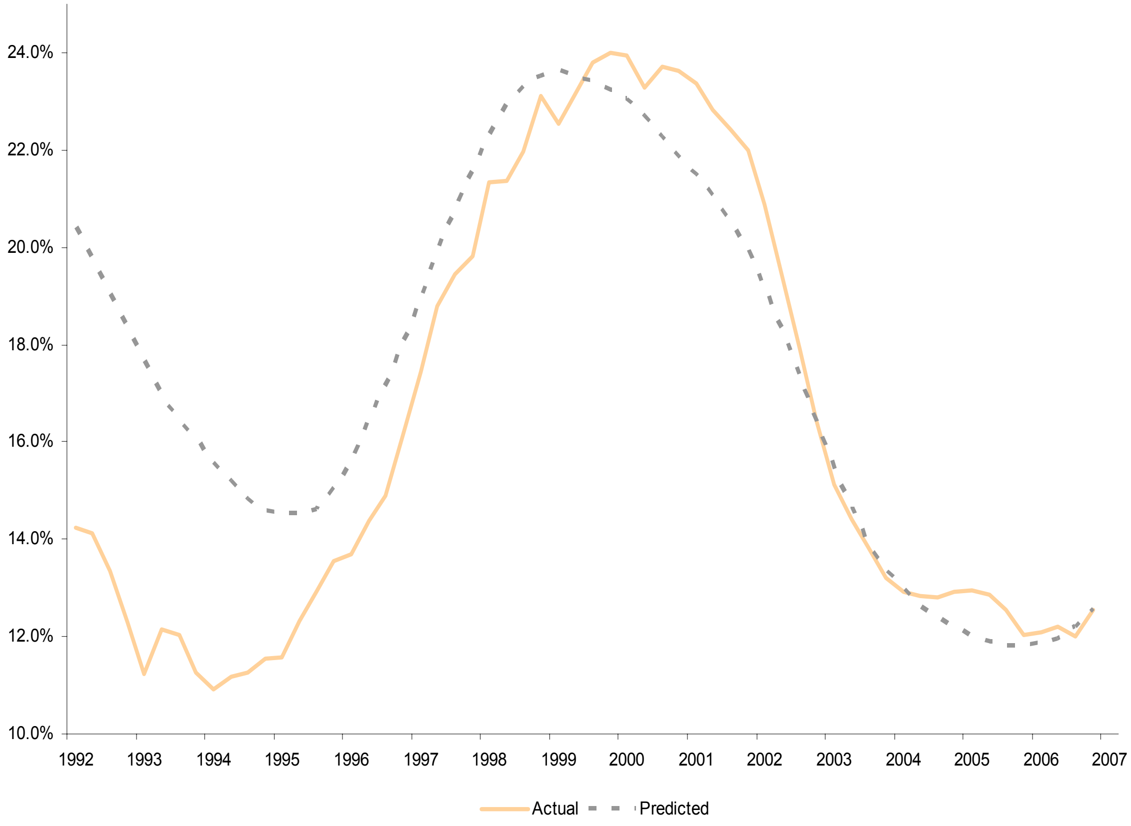
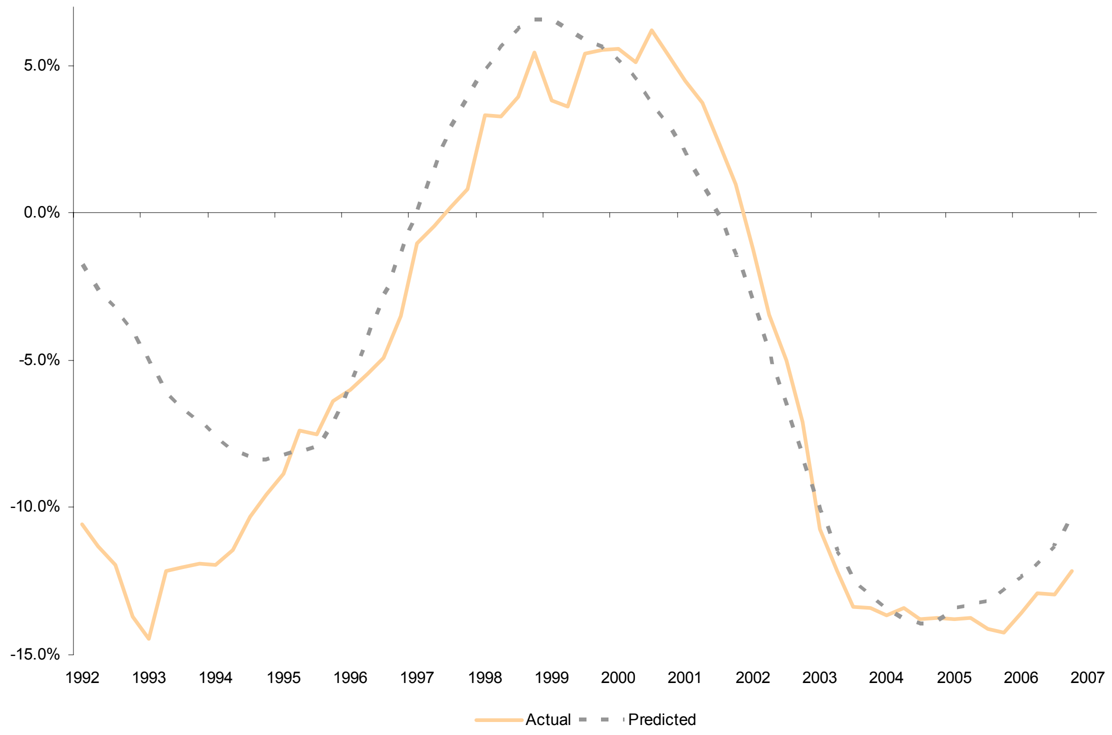


Figure 4: Five Year Cumulative Downgrade Rate and Model Forecast

Figure 5: Five Year Cumulative Net Drift and Model Forecast



III Forecast Assumptions

The Credit Transition Model conditions on recent rating history and the future path of two economic drivers: the unemployment rate, and the high yield spread. The rating characteristics essential to the model include an issuer's current rating, how long it has maintained that rating, and whether it was upgraded or downgraded into that rating. For the current global portfolio, these attributes are summarized in Table 3. As an example, Aa1 rated issuers comprise 4.2% of all issuers in the global portfolio. Of those, 52.7% were upgraded into the Aa1 rating, and 10.2% were downgraded (the rest, of course, are original issue Aa1). Furthermore, the average time spend in the Aa1 rating is now 16 quarters.

Table 3: Current Rating Characteristics for the Global Portfolio

	Share of Population	Last Rating Action		Average Duration
		Upgrade	Downgrade	
Aaa	2.7%	39.4%		25
Aa1	4.2%	52.7%	10.2%	16
Aa2	3.8%	46.8%	16.9%	10
Aa3	9.9%	23.8%	10.0%	8
A1	12.6%	20.2%	6.7%	7
A2	7.1%	43.2%	23.5%	11
A3	6.0%	38.2%	31.6%	10
Baa1	6.3%	38.6%	32.6%	9
Baa2	6.3%	31.5%	38.5%	9
Baa3	5.2%	31.9%	38.3%	9
Ba1	3.0%	40.2%	29.6%	7
Ba2	3.2%	45.7%	24.6%	5
Ba3	3.8%	41.7%	20.8%	5
B1	5.0%	31.9%	23.3%	4
B2	6.3%	18.6%	23.9%	5
B3	8.1%	10.7%	21.2%	4
Caa1	4.2%	9.8%	38.6%	3
Caa2	1.6%	4.0%	52.5%	3
Caa3	0.4%	3.8%	69.2%	5
Ca	0.2%	0.0%	100.0%	3
C	0.1%		100.0%	8
	100%			

Population shares sum to 100%
Upgrade (downgrade) percent is the share of currently like-rated issuers which were upgraded (downgraded) into that rating.
Average duration is measured in quarters.

Additionally, the model requires forecasts of the U.S. unemployment rate and the high yield spread over Treasuries. Figure 6 presents the recent history and our current baseline, positive and negative scenario forecasts for the unemployment rate; Figure 7 presents the high yield spread. These forecasts are illustrative only: they are the result of a simple VAR specification, and should not be interpreted as "optimal" in any way, neither as representing Moody's true opinion of the likely future paths of these series.

The significance of the economic forecasts increases with the horizon. When studying transitions over short horizons, the rating information is far more important. But over long horizons, different economic forecasts can induce substantially different model results.

Figure 6: Unemployment Forecast: Baseline, Positive and Negative Scenarios (percent)

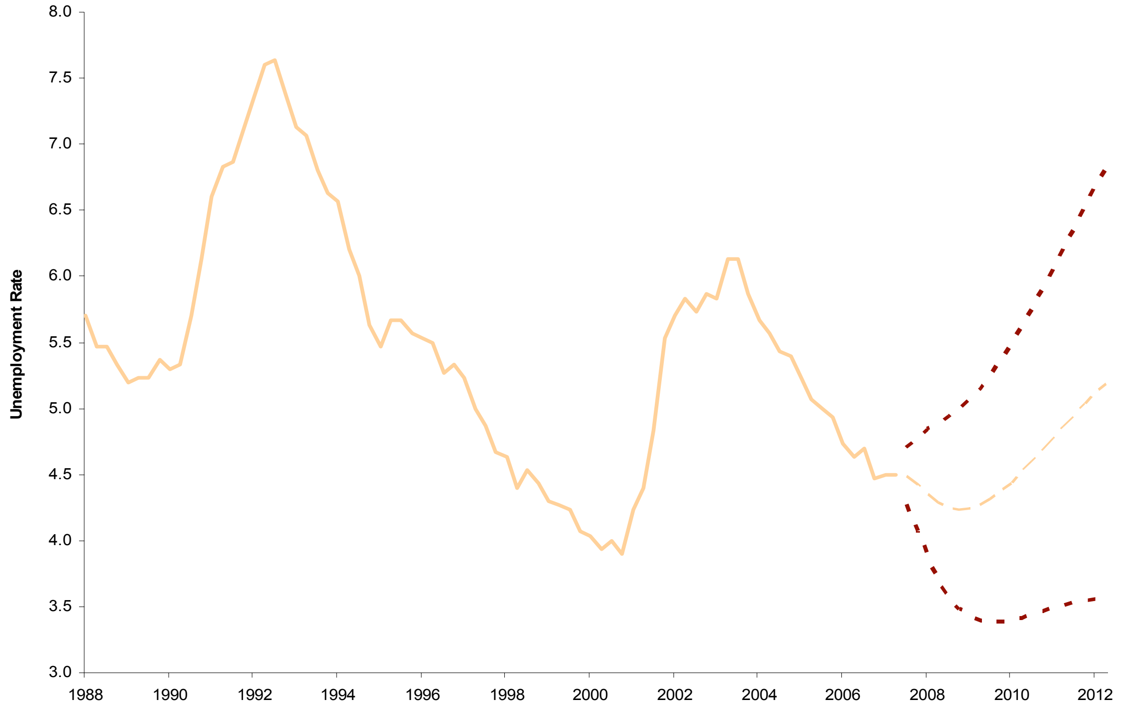
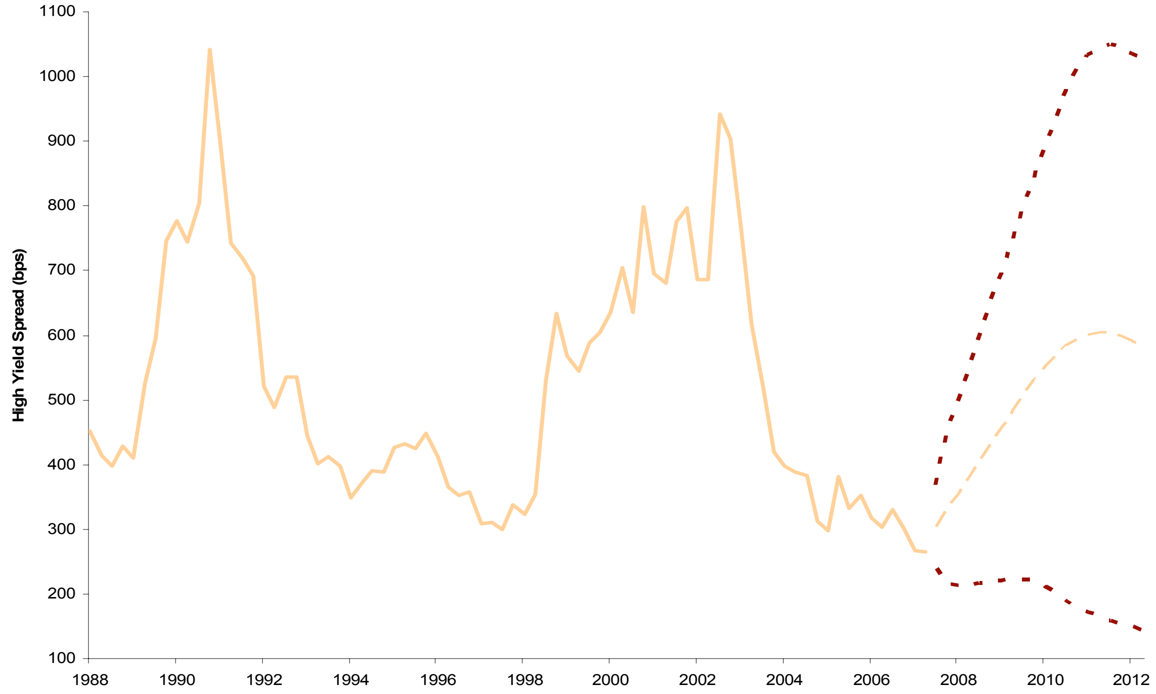


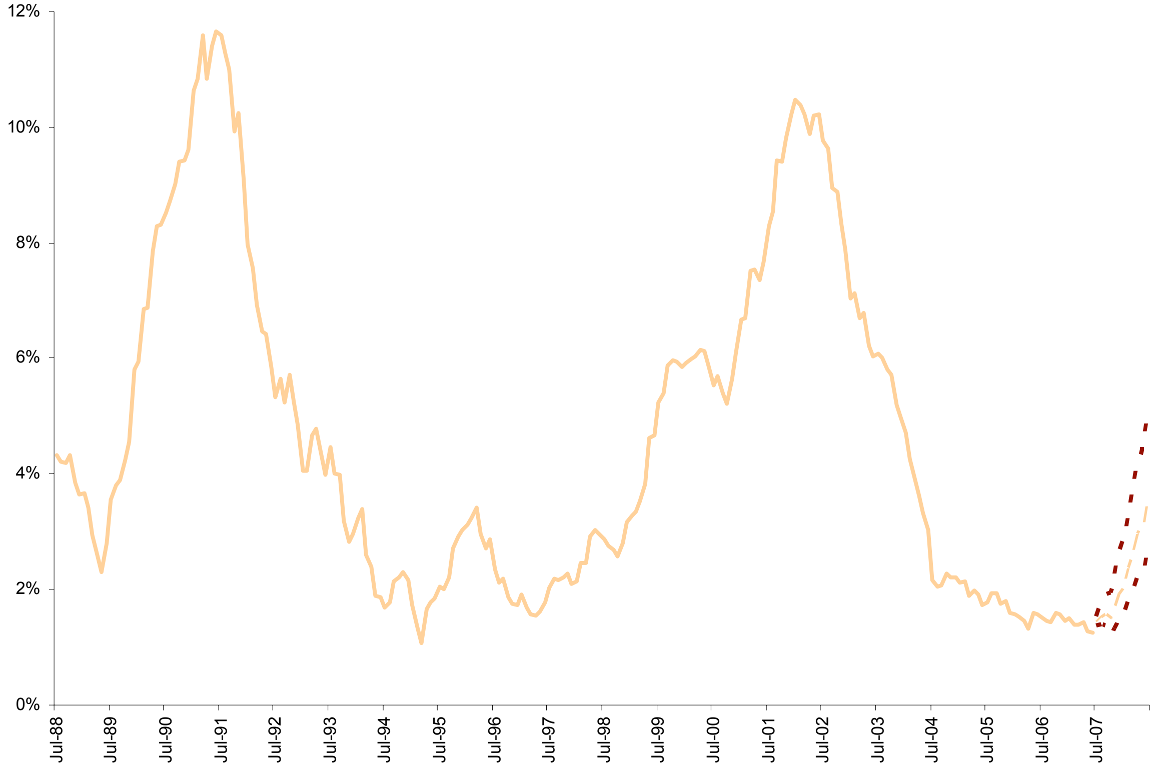
Figure 7: High Yield Spread Forecast: Baseline, Positive and Negative Scenarios (in bps)



IV Default Forecasts

Perhaps the most common use of the model is to forecast the probability of default for a given portfolio over a given horizon. If, for example, the portfolio is all speculative-grade (SG) credits, and if the horizon is one year, then this model would be generating the one year global SG default rate which, of course, has been a fixture of the Monthly Default Report. Figure 8 presents a forecast as of July 1, 2007. There is a baseline forecast bounded by positive and negative economic scenarios.[7] Incorporating this uncertainty over the future path of the economy represents an enhancement with respect to Moody's time-series default model.

Figure 8: One Year Global SG Default Rate: Baseline, Positive and Negative Scenarios



One of the advantages of this issuer-based model is that we can study subgroups of interest. In particular, we can study different geographic subsets of the global universe. Figures 9 and 10 are analogous to Figure 8, but they cover the United States and European portfolios, respectively. Not surprisingly, the United States default rates are quite similar to the global, since it is the largest subset of issuers. The European portfolio, however, behaves quite differently both historically and in expectation.

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[7] These particular default forecasts use a simple auxiliary VAR to forecast the unemployment rate and the high yield spread. Our economic forecast is essentially "mean reversion" subject to some conditioning on things like industrial productivity, stock market returns, and the slope of the Treasury yield curve. A better, more sophisticated economic model might yield a different (and better) baseline forecast.

Figure 9: One Year U.S. SG Default Rate: Baseline, Positive and Negative Scenarios

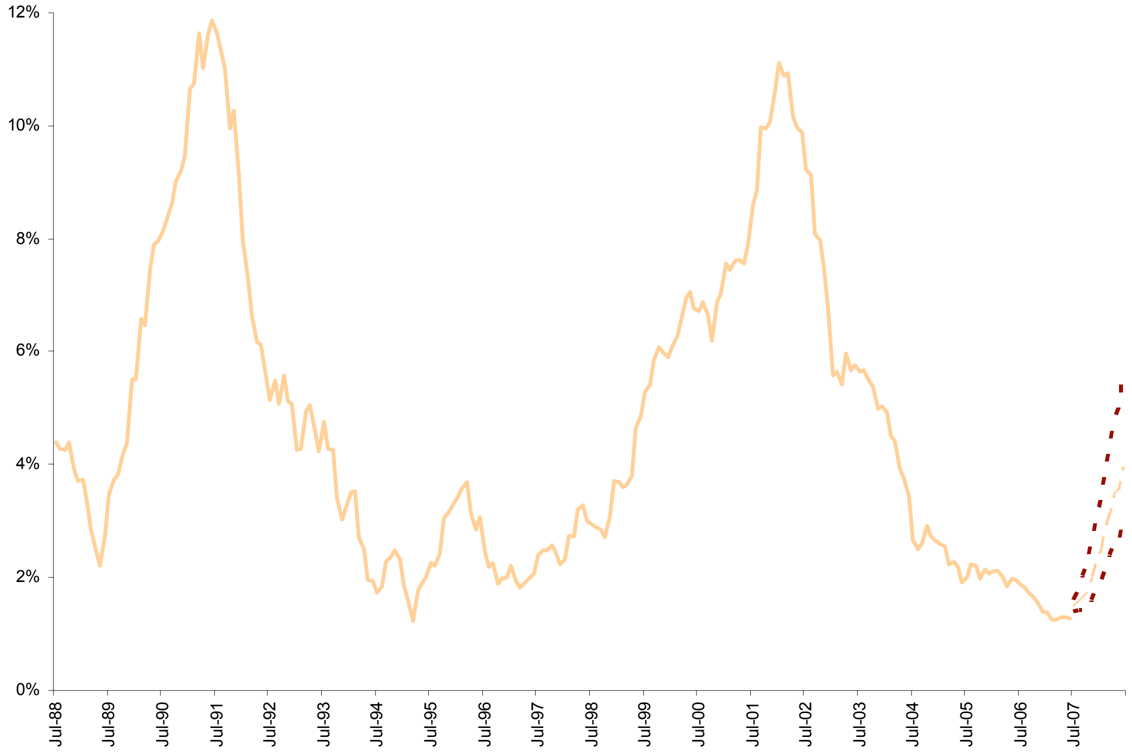
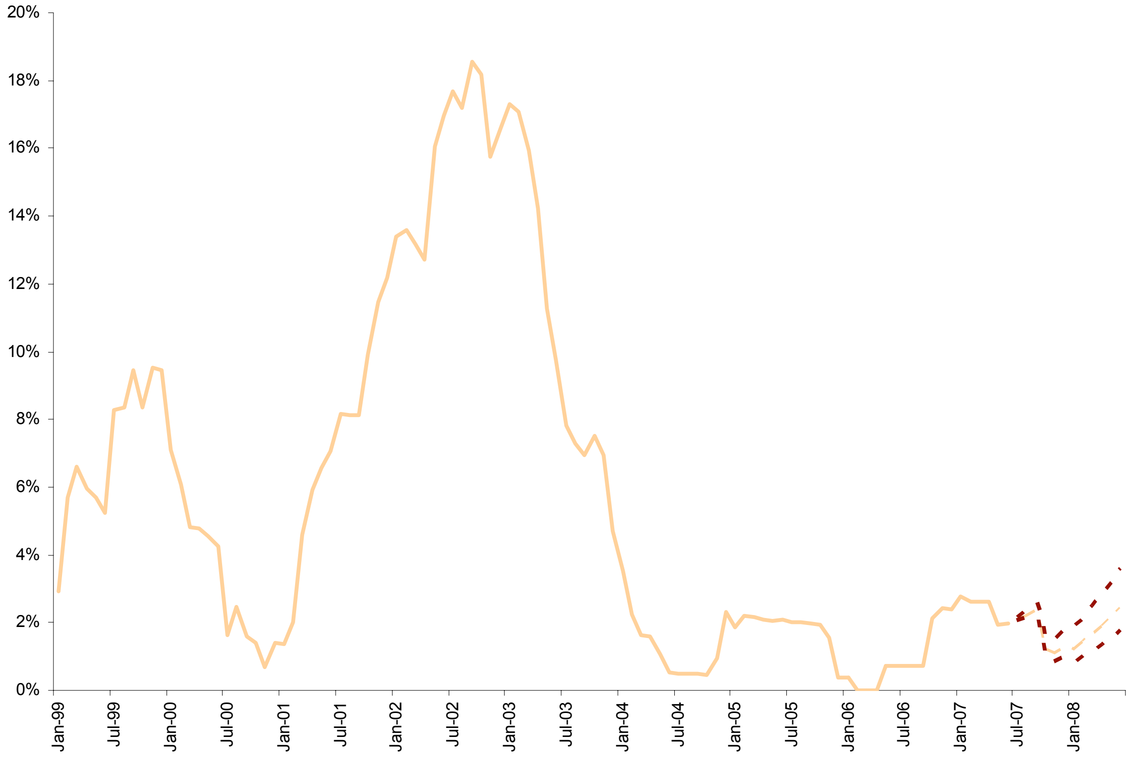


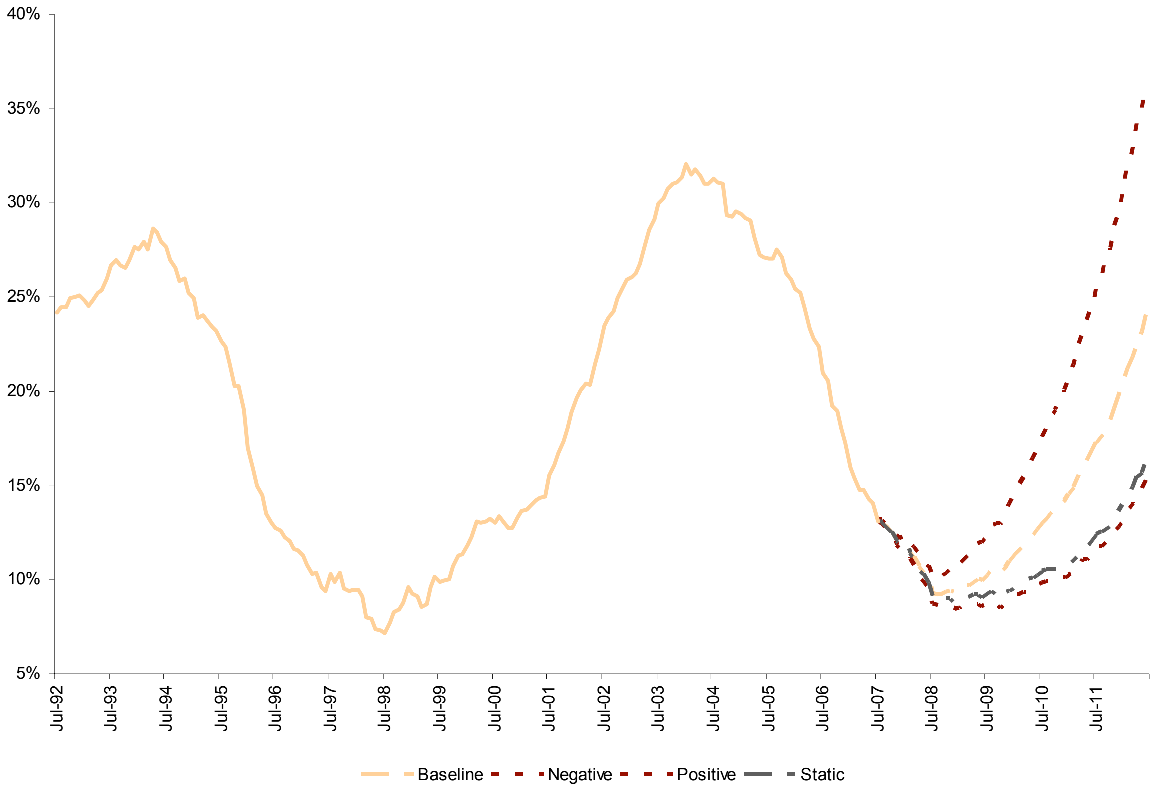
Figure 10: One Year European SG Default Rate: Baseline, Positive and Negative Scenarios



Yet another enhancement of the new model is that it may be applied to other time horizons. Figure 11 is analogous to Figure 9 except that the horizon is now five years, not one. Figure 12 presents the European portfolio. In addition to the three economic scenarios of the earlier figures, there is now a "static expectations" forecast. This is the expected default rate under the assumption that the unemployment rate and the high yield spread remain unchanged at their current levels for the next five years. Such a "forecast," of course, is provided as a benchmark or reference.

We should stress that these are cumulative default rates for the current cohort of issuers. Figure 11 indicates that of the current U.S. SG portfolio, about 25% should be expected to default by July 1, 2012 within a likely range of 20 – 35%.[8] It does *not* indicate that the "default rate" in the second quarter of 2012 is going to be anywhere near 25%.

Figure 11: Five Year U.S. SG Cumulative Default Rate: Baseline, Positive, Negative and Static Scenarios



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[8] These default forecasts have been adjusted for withdrawal probabilities. We almost certainly will not observe 25% of the current universe entering default – many will have their ratings withdrawn over the next five years.

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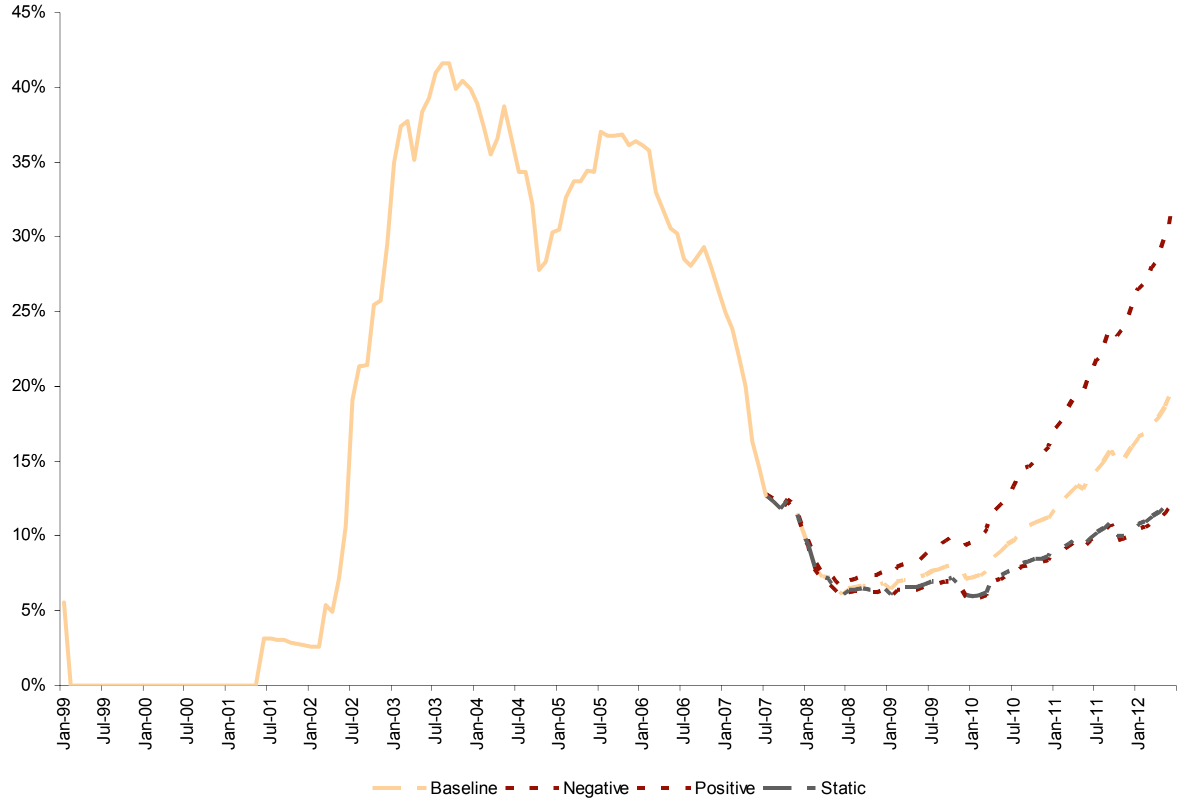
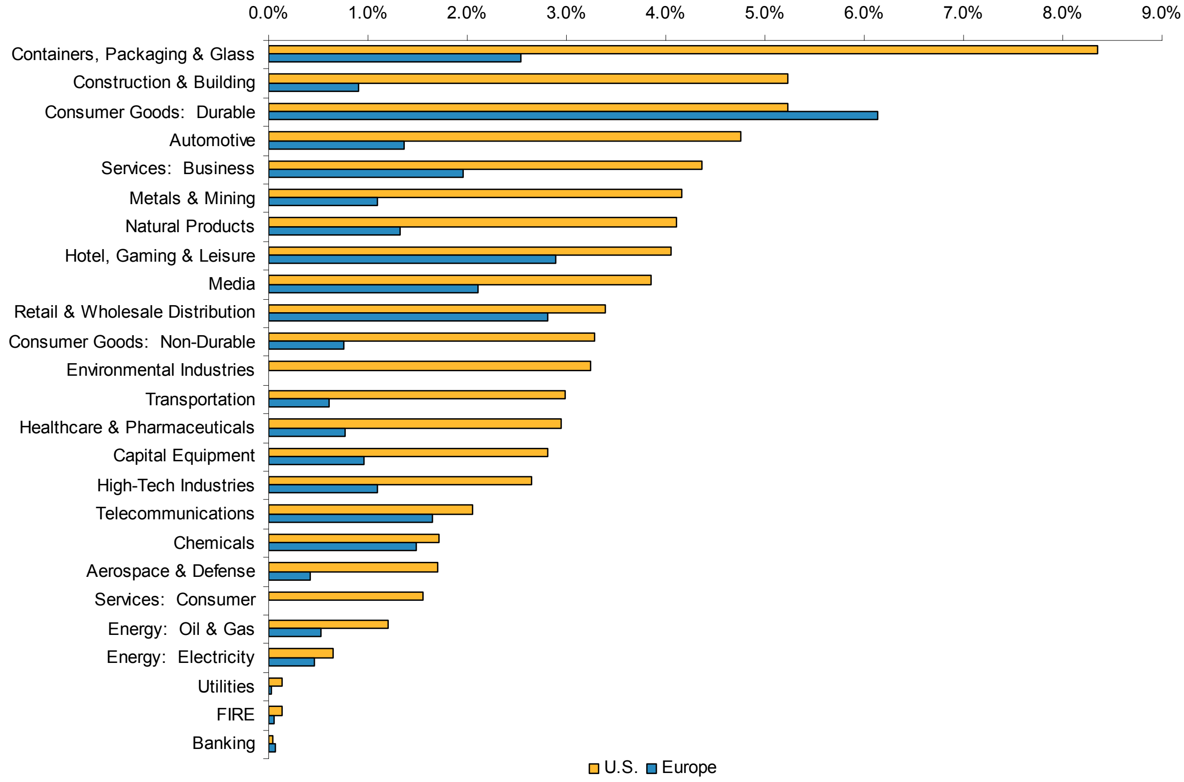
Figure 12: Five Year European SG Cumulative Default Rate: Baseline, Positive, Negative and Static Scenarios



As a final example of the portfolio flexibility of the new Credit Transition Model, Figure 13 compares expected one year default rates by industry for the U.S. and Europe. Unlike the default rates presented previously, these are not speculative-grade default rates, but whole industry default rates. Since the economic forecast is the same in all cases, the principal difference across industries highlighted in this Figure is the different ratings mix – not just the level of ratings, but the recent upgrade and downgrade activity as well as how long issuers have held their current ratings. Figure 13 would suggest, for example, that a random issuer from the U.S. Automotive industry has about a 4.6% probability of default over the next year, compared with about 1.4% for a random European Automotive issuer.

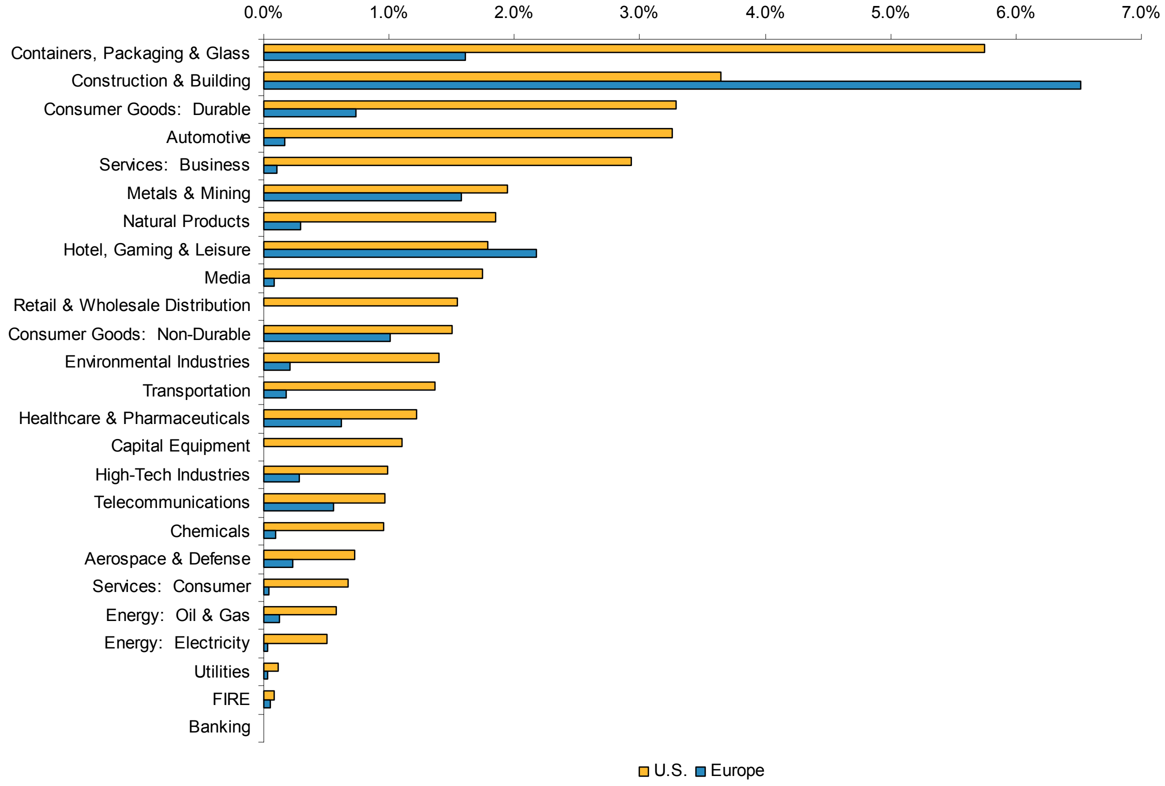
Introducing Moody's Credit Transition Model

Figure 13: One Year Forecasted Default Rate by Industry (Issuer-Weighted)



The forecasts in Figure 13 are issuer-weighted, but nothing precludes us from using the model to provide dollar volume-weighted default forecasts. These are presented in Figure 14. We can interpret this as saying that a randomly selected dollar of debt from the U.S. Automotive industry has a 3.3% chance of default over the next year, versus 0.2% for a random dollar of European Automotive debt.

Figure 14: One Year Forecasted Default Rate by Industry (Volume-Weighted)



These exhibits highlight the increased functionality of the Moody's Credit Transition Model, especially when compared to its older time-series global SG default model. First, they may be aggregated to different portfolios based on geography, industry, and rating. Second, they may be extended to variable time horizons. Third, the same model may be used to generate either issuer- or volume-weighted default rates. All of these applications are mutually consistent.

The Credit Transition Model is exactly that – a model of all credit transitions, not just default. In some cases, upgrades or (more likely) downgrades are important credit events themselves. Table 4 presents a forecast of rating transitions for the global rated universe over the next year. It includes transitions to the absorbing states of *default* and *withdrawal*. It would suggest that on average, conditional on our benchmark economic forecast, issuers currently rated Baa3 have a 76.2% chance of being rated Baa3 one year from now, an 8.3% chance of upgrading to Baa2, a 3.3% chance of downgrading to Ba1, a 4.6% chance of withdrawing and a 0.2% chance of defaulting.

Introducing Moody's Credit Transition Model

Table 4: One Year Forecasted Global Transition Probabilities (Percent)

												To Rating										
		Aaa	**Aa1**	**Aa2**	**Aa3**	**A1**	**A2**	**A3**	**Baa1**	**Baa2**	**Baa3**	**Ba1**	**Ba2**	**Ba3**	**B1**	**B2**	**B3**	**Caa1**	**Caa2**	**Caa3**	**Ca-C**	***WR***	***DEF***
From Rating	**Aaa**	**92.4**	2.2	1.3	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.8	0.0
	Aa1	4.3	**84.4**	4.6	2.0	0.3	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.4	0.0
	Aa2	1.4	5.7	**78.4**	5.8	1.2	0.4	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6.9	0.0
	Aa3	0.1	1.0	4.1	**83.6**	3.5	1.3	0.4	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6.0	0.0
	A1	0.0	0.1	0.4	5.7	**82.9**	4.1	1.7	0.5	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.3	0.0
	A2	0.0	0.0	0.2	1.0	5.0	**82.9**	4.1	1.4	0.4	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.5	0.0
	A3	0.1	0.1	0.1	0.2	0.9	7.6	**78.7**	4.5	2.1	0.7	0.2	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.5	0.0
	Baa1	0.1	0.1	0.1	0.1	0.2	1.7	5.9	**79.8**	5.0	1.7	0.4	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	4.4	0.1
	Baa2	0.1	0.1	0.1	0.1	0.1	0.7	1.6	5.5	**78.6**	5.1	1.2	0.7	0.4	0.2	0.1	0.1	0.0	0.0	0.0	0.0	5.2	0.0
	Baa3	0.1	0.0	0.0	0.0	0.2	0.5	0.6	2.2	8.3	**76.2**	3.3	1.9	1.0	0.4	0.2	0.1	0.1	0.0	0.0	0.0	4.6	0.2
	Ba1	0.0	0.0	0.1	0.1	0.5	0.4	0.4	1.2	4.1	13.8	**59.8**	3.9	3.4	1.3	0.9	0.5	0.2	0.1	0.0	0.1	9.2	0.2
	Ba2	0.0	0.0	0.1	0.1	0.2	0.3	0.2	0.5	1.2	4.5	11.2	**58.6**	4.8	2.9	2.1	1.2	0.7	0.2	0.1	0.2	10.6	0.5
	Ba3	0.0	0.0	0.1	0.1	0.0	0.3	0.2	0.2	0.6	1.2	3.8	9.5	**60.6**	4.1	4.3	1.9	0.7	0.4	0.2	0.1	11.1	0.5
	B1	0.0	0.0	0.0	0.0	0.1	0.2	0.1	0.3	0.2	0.4	1.0	2.9	8.5	**63.1**	5.4	4.1	1.6	0.9	0.3	0.2	10.0	0.8
	B2	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.2	0.2	0.2	0.4	0.8	2.5	7.8	**65.8**	5.3	3.0	1.6	0.6	0.4	9.4	1.6
	B3	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.3	0.5	3.0	6.2	**64.9**	4.1	3.6	1.0	1.1	11.5	3.1
	Caa1	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.2	0.2	0.7	2.3	5.8	**55.0**	4.5	3.6	2.5	17.1	7.7
	Caa2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.4	0.2	0.0	0.5	0.6	0.8	2.8	3.4	**51.4**	2.3	4.2	19.2	14.0
	Caa3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.4	0.0	0.1	1.4	0.5	1.4	3.3	4.8	**40.1**	5.7	23.9	18.3
	Ca-C	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.1	0.3	0.7	0.4	1.2	2.2	**35.3**	35.2	24.4

As was the case with the default forecasts presented in Section III, nothing precludes us from considering transitions for different portfolios or different horizons under different economic scenarios. Since the point has been demonstrated above, here we will only demonstrate the horizon flexibility by presenting a five year transition forecast in Table 5.

Note also that since we have an explicit withdrawal forecast, we can adjust these transition rates in a manner similar to our adjustment to default statistics.[9] An example of such a withdrawal-adjusted transition table for the same universe, horizon, and economic forecast of Table 5 is presented in Table 6. The impact of the adjustment is considerable.

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[9] For a comprehensive discussion of withdrawal adjustment, please see Cantor and Hamilton (2007).

Table 5: Five Year Forecasted Global Transition Probabilities (Percent)

To Rating

From Rating	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3	Caa1	Caa2	Caa3	Ca-C	*WR*	*DEF*
Aaa	**63.1**	8.1	5.7	2.8	0.8	0.6	0.2	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	18.4	0.0
Aa1	11.2	**39.4**	12.1	9.8	3.2	1.4	0.6	0.2	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	21.8	0.0
Aa2	4.8	10.4	**28.9**	15.4	5.6	3.0	1.2	0.6	0.4	0.3	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	29.2	0.0
Aa3	1.1	3.3	7.3	**37.9**	9.7	5.7	2.7	1.2	0.7	0.3	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	29.8	0.0
A1	0.3	0.8	2.0	10.8	**35.4**	11.8	6.7	3.5	2.0	0.9	0.3	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	0.0	24.6	0.1
A2	0.1	0.4	1.0	3.9	9.5	**38.5**	11.2	6.4	3.7	1.9	0.6	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.0	0.0	21.2	0.3
A3	0.4	0.3	0.5	1.4	3.7	13.8	**30.7**	11.2	7.8	4.3	1.3	0.8	0.6	0.4	0.4	0.2	0.1	0.1	0.1	0.1	21.5	0.4
Baa1	0.3	0.3	0.3	0.7	1.4	5.8	10.3	**32.4**	12.5	7.2	2.2	1.3	1.1	0.7	0.6	0.4	0.2	0.2	0.1	0.1	21.2	0.8
Baa2	0.2	0.3	0.2	0.5	0.8	2.9	4.7	10.1	**30.7**	11.9	3.7	2.4	2.0	1.3	1.2	0.8	0.5	0.3	0.1	0.2	23.9	1.2
Baa3	0.2	0.2	0.1	0.4	0.8	2.0	2.8	6.3	13.7	**27.9**	5.6	3.8	3.1	2.0	1.9	1.3	0.8	0.5	0.2	0.3	23.9	2.2
Ba1	0.1	0.1	0.2	0.4	0.9	1.4	1.7	3.8	8.3	12.7	**11.7**	4.3	4.3	3.0	3.0	2.1	1.3	0.9	0.4	0.4	35.5	3.6
Ba2	0.1	0.1	0.1	0.3	0.5	0.9	1.0	2.2	4.6	8.1	6.2	**9.3**	4.9	4.1	4.2	3.0	1.9	1.3	0.6	0.6	39.8	6.3
Ba3	0.0	0.1	0.2	0.2	0.3	0.7	0.6	1.2	2.5	4.4	4.4	5.2	**10.2**	4.9	5.5	3.8	2.3	1.6	0.7	0.7	42.6	7.8
B1	0.1	0.0	0.1	0.1	0.3	0.5	0.4	0.8	1.3	2.3	2.6	3.6	5.4	**11.3**	6.1	5.0	2.9	2.1	0.8	0.9	42.5	11.0
B2	0.0	0.1	0.1	0.1	0.1	0.3	0.4	0.6	0.8	1.2	1.4	2.0	3.5	5.7	**12.4**	5.3	3.3	2.4	1.0	1.0	43.1	15.2
B3	0.0	0.1	0.1	0.1	0.1	0.1	0.2	0.3	0.4	0.6	0.6	1.0	1.8	3.5	4.8	**9.1**	3.0	2.6	1.0	1.1	48.3	21.2
Caa1	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.2	0.3	0.3	0.5	0.8	1.6	2.3	2.8	**2.4**	1.5	0.8	0.8	58.5	26.8
Caa2	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.3	0.5	0.3	0.4	0.6	0.9	1.3	1.7	1.0	**1.5**	0.5	0.6	57.6	32.4
Caa3	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.2	0.3	0.3	0.3	0.6	1.0	1.0	1.3	0.9	0.9	**0.6**	0.5	57.5	34.5
Ca-C	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.2	0.3	0.4	0.5	0.3	0.3	0.2	**0.3**	62.7	34.4

Table 6: Five Year Forecasted Global Transitions Probabilities (withdrawal-adjusted) (Percent)

To Rating

From Rating	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3	Caa1	Caa2	Caa3	Ca-C	*DEF*
Aaa	**77.4**	9.9	7.0	3.4	1.0	0.8	0.2	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Aa1	14.4	**50.4**	15.4	12.5	4.0	1.8	0.7	0.3	0.2	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Aa2	6.8	14.7	**40.8**	21.8	8.0	4.2	1.8	0.8	0.5	0.4	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Aa3	1.5	4.6	10.4	**54.0**	13.9	8.1	3.9	1.8	0.9	0.4	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.1
A1	0.4	1.1	2.7	14.3	**47.0**	15.7	8.9	4.6	2.6	1.2	0.4	0.2	0.3	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.1
A2	0.2	0.5	1.2	5.0	12.1	**48.9**	14.2	8.2	4.7	2.5	0.7	0.4	0.4	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.3
A3	0.5	0.4	0.6	1.8	4.7	17.5	**39.2**	14.2	9.9	5.4	1.7	1.0	0.8	0.5	0.5	0.3	0.2	0.1	0.1	0.1	0.5
Baa1	0.4	0.4	0.4	0.8	1.7	7.4	13.1	**41.2**	15.9	9.1	2.8	1.7	1.3	0.9	0.7	0.5	0.3	0.2	0.1	0.1	0.9
Baa2	0.3	0.4	0.3	0.7	1.0	3.8	6.2	13.2	**40.5**	15.7	4.9	3.2	2.6	1.7	1.5	1.0	0.7	0.4	0.2	0.2	1.4
Baa3	0.3	0.2	0.2	0.5	1.1	2.6	3.6	8.2	18.0	**36.9**	7.4	5.0	4.1	2.7	2.5	1.7	1.1	0.7	0.3	0.4	2.7
Ba1	0.2	0.2	0.2	0.6	1.3	2.2	2.7	5.9	12.9	19.7	**18.5**	6.8	6.8	4.7	4.7	3.3	2.0	1.3	0.6	0.7	4.8
Ba2	0.1	0.1	0.2	0.4	0.9	1.6	1.7	3.6	7.7	13.7	10.5	**15.8**	8.4	7.0	7.1	5.1	3.2	2.1	0.9	1.1	8.8
Ba3	0.1	0.1	0.3	0.3	0.5	1.3	1.1	2.2	4.4	7.9	7.9	9.3	**18.4**	8.8	10.0	6.9	4.1	2.9	1.2	1.3	11.1
B1	0.1	0.1	0.1	0.2	0.5	1.0	0.7	1.5	2.3	4.1	4.7	6.6	9.9	**20.6**	11.0	9.1	5.2	3.8	1.5	1.6	15.4
B2	0.1	0.1	0.2	0.2	0.2	0.5	0.7	1.1	1.5	2.2	2.6	3.8	6.6	10.7	**23.6**	10.1	6.3	4.5	1.9	1.9	21.1
B3	0.1	0.2	0.3	0.1	0.2	0.3	0.5	0.7	0.9	1.4	1.5	2.2	4.0	7.9	10.8	**20.7**	6.8	5.8	2.2	2.4	30.8
Caa1	0.0	0.1	0.1	0.1	0.2	0.5	0.3	0.5	0.7	1.2	1.2	1.7	3.0	5.9	8.5	10.6	**9.0**	5.6	2.9	2.8	44.9
Caa2	0.0	0.1	0.1	0.1	0.1	0.3	0.3	0.7	1.5	2.5	1.5	1.6	2.9	4.4	5.8	8.0	4.5	**6.9**	2.2	2.8	53.7
Caa3	0.0	0.0	0.1	0.1	0.1	0.3	0.2	0.5	0.9	1.7	1.6	1.7	2.9	5.2	5.3	7.0	4.6	4.5	**2.9**	2.7	57.6
Ca-C	0.0	0.0	0.1	0.0	0.1	0.2	0.2	0.3	0.6	1.1	1.1	1.2	2.3	3.5	4.1	5.6	3.6	4.3	2.5	**3.3**	66.0

Withdrawn ratings represent censored observations: we do not know what would have happened to the rating had it remained outstanding. We assume that this censoring is neutral with respect to the underlying credit risk. In other words, a withdrawn B3 issuer is not any more or less risky than a similar outstanding B3 issuer. As such, we impute to the withdrawn state the same pattern of upgrades, downgrades and default that we expect for the fully-observed states. The Credit Transition Model has the flexibility to allow alternative assumptions about withdrawal.

Transition tables such as Table 5 should be read as saying that five years from now, we have a 27.9% probability of observing a Baa3 rating for those issuers currently rated Baa3. It should *not* be read as saying that there is a 27.9% chance that currently rated Baa3 issuers will have no rating action over the next five years. In the case of horizons as short as one year, those two statements are going to be very nearly identical, but they are logically distinct. And that distinction becomes material over long horizons. We will now consider these first-passage probabilities.

Suppose we manage a portfolio of credits subject to the requirement that they be investment-grade: as soon as a rating migrates below Baa3, that credit must exit our portfolio. Suppose we have in that portfolio a credit which was just downgraded to A3. We want to know the probability that this credit will become speculative-grade over the next five years.

Can we use a transition matrix to solve this problem? Certainly not in practice. We know that we need a matrix which covers our horizon of interest, conditions on the economy, and conditions on the fact that this credit was *downgraded* to A3 and is thus more likely than average to experience further downgrades. Such conditional transition statistics are not generally available. But suppose they were. Would that be enough to determine the first-passage probability? Are cumulative transition rates – even of the "best" kind – the same thing as first-passage probabilities?

Table 7 presents transition probabilities for a downgraded A3 issuer under our benchmark economic forecast. It indicates an 8.0% probability of being rated SG five years from now, a probability which covers our horizon of interest, is conditional on the economy, and is conditional on the fact that the issuer was downgraded. Is "8.0%" a good estimate of the probability that this credit will become SG? We quickly note several problems:

1. *Default*: There is a 1.0% probability of defaulting. While it is probably a safe assumption that ratings first migrate to SG before defaulting, it is an assumption nonetheless. How would we treat defaults if our investment threshold were B3 instead of Baa3? In that case, there would be a non-zero probability of defaulting without having first crossed below B3.
2. *Withdrawal*: There is a 21.3% chance of withdrawing. That is divided – in an unknown way – between migrating to SG before withdrawing and not migrating to SG before withdrawing. What should we assume about that mix?[10]
3. *Reversal*: There is some possibility – however remote – that the rating could fall below Baa3 but then rise above it over the next five years. Such a migration would trigger our investment restrictions, but these probabilities are nowhere to be found in Table 7. It is probably safe to ignore this probability over short- and medium-horizons, but what about long horizons?

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[10] Moody's research indicates that rating withdrawal is a neutral event in the sense that a B3 issuer that withdraws is not "riskier" than a B3 issuer which does not withdraw. But it remains true that lower-rated credits are more likely to withdraw. Hence it is somewhat *more* likely than average that states of the world which lead to withdrawal include passage into SG than not.

Table 7: Cumulative Transition Probabilities for a Downgraded A3 Issuer Under Baseline Scenario

	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	1
A1	0	0	1	1	2	2
A2	0	2	5	8	9	9
A3	91	73	55	40	32	25
Baa1	5	13	16	17	16	15
Baa2	2	6	10	11	12	11
Baa3	1	2	4	6	7	7
Ba1	0	1	1	2	2	2
Ba2	0	0	1	1	1	1
Ba3	0	0	0	1	1	1
B1	0	0	0	0	1	1
B2	0	0	0	0	1	1
B3	0	0	0	0	0	1
Caa1	0	0	0	0	0	0
Caa2	0	0	0	0	0	0
Caa3	0	0	0	0	0	0
Ca	0	0	0	0	0	0
C	0	0	0	0	0	0
WR	*0.6*	*2.9*	*6.2*	*10.4*	*15.5*	*21.3*
Def	*0.0*	*0.1*	*0.2*	*0.4*	*0.7*	*1.0*

The actual first-passage probability as indicated by the Credit Transition Model is 12.2%. Even if we add the cumulative default probability (1%) to the cumulative SG probability (8%) and adjust for withdrawal in our usual way, our estimate is only 10.9% - much closer, but still short. And we must reiterate that none of this is actually possible using published historical transition matrices. Only a tool like the Credit Transition Model can provide the appropriate conditional cumulative transitions, and only the Credit Transition Model can actually go beyond simple cumulative transition rates to a proper calculation of first-passage probabilities.

This first-passage analysis yields a meaningful marginal probability of falling into SG *in each particular quarter* over the next five years by simply differencing the cumulative probabilities. In short, we can obtain the probability that this issuer first becomes spec-grade in quarter 17 conditional on not having done so before. These cannot be obtained from the available transition probabilities, since the absorbing withdrawal and default states imply that, at least eventually, the cumulative transition probability will decrease, and hence the implied marginal probability will be negative.

V Portfolio Analysis

We return our attention to the default forecasts of the model, and briefly consider portfolio analytics. The Credit Transition Model will output a cumulative default probability for any arbitrary portfolio of rated credits. The results can be used as primary inputs in a portfolio risk application. For these examples, we will consider the five year default probability (adjusted for withdrawal) for the portfolio of 76 U.S. Automotive credits under our baseline economic forecast.

The Moody's Credit Transition Model provides issuer-specific default probabilities, not just portfolio averages. Taking this heterogeneity into account when evaluating portfolio losses can be important. For example, the average default probability for the Automotive portfolio we are considering is 24.1%, suggesting

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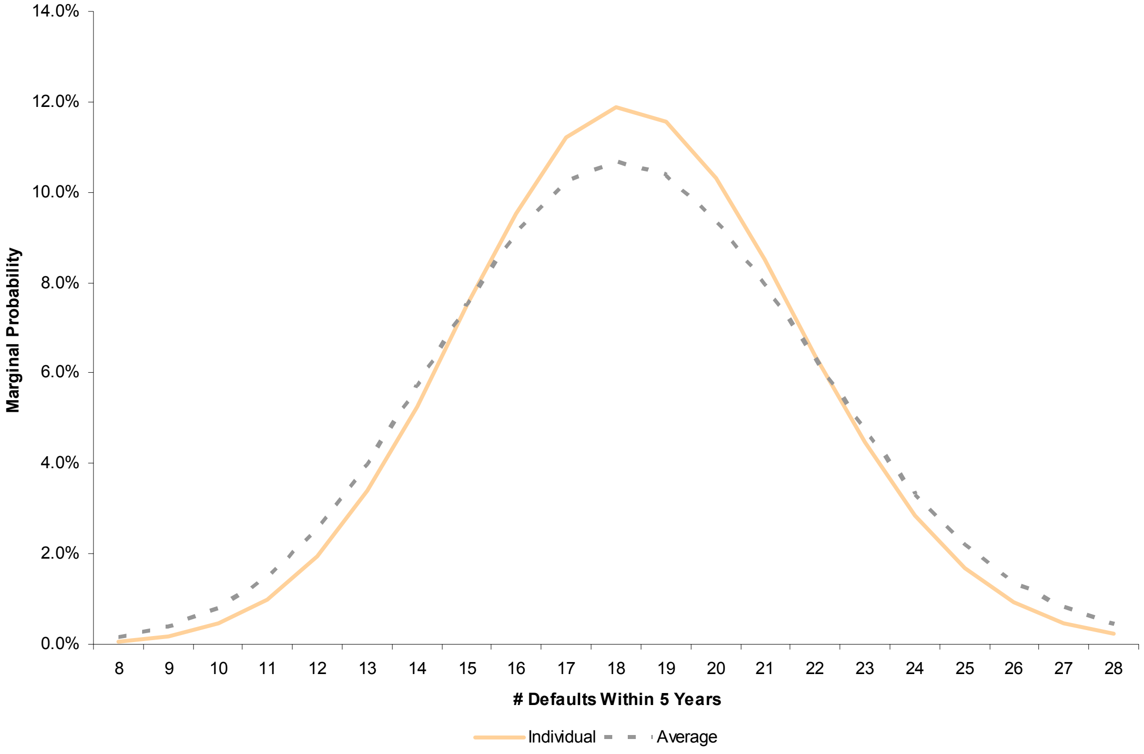
18 defaults out of our portfolio of 76 credits over the next five years. But the *individual* default probabilities range from essentially 0% to as high as 73.7%: some credits almost certainly will default, and others almost certainly will not. Figure 15 compares the default distribution using a binomial model centered on the portfolio's average probability versus a Monte Carlo simulation applied to the individual probabilities. We see, as is always the case, that using the portfolio average overstates the tail losses (understates the modal loss).

Figure 15: Comparing Estimates of Marginal Portfolio Loss Distributions



Some might regard the use of the portfolio average as conservative, since it "overstates" the marginal probability of observing large losses. That is true, but it also overstates the probability of observing small losses. When we look at the cumulative probability distributions in Figure 16, we see that the estimate based on the portfolio average exceeds the issuer-specific estimate for losses up to about 19, after which the issuer-specific estimate exceeds the average. This is easier to see in Figure 17 which plots the difference between the two.

Figure 16: Comparing Estimates of Cumulative Portfolio Loss Estimates

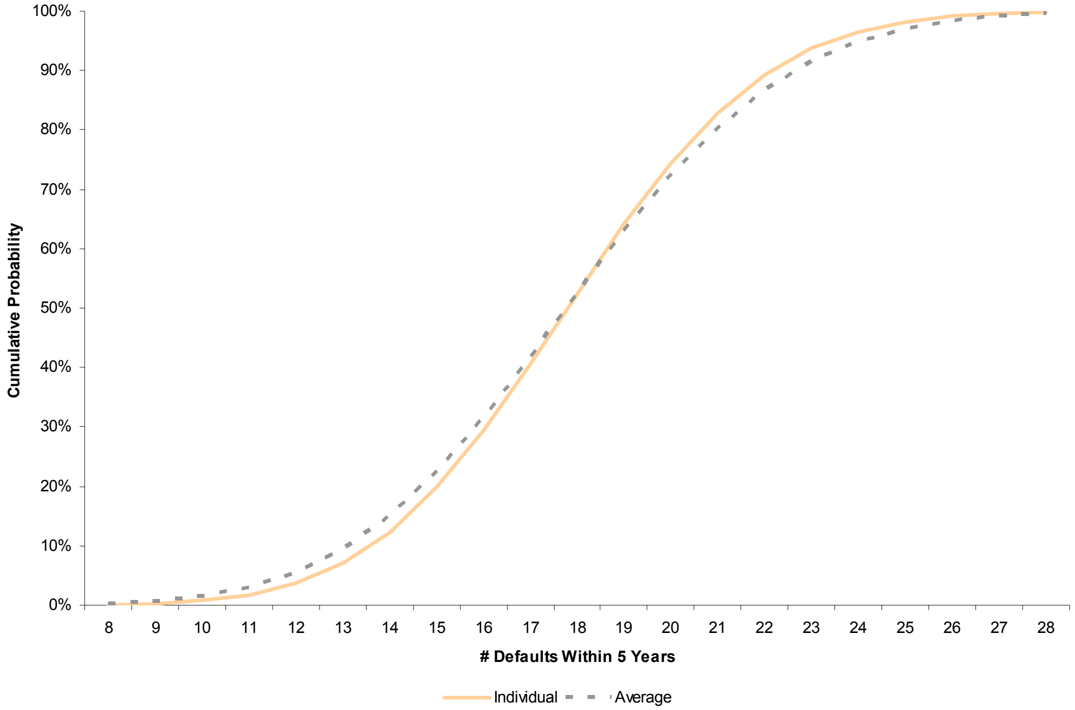
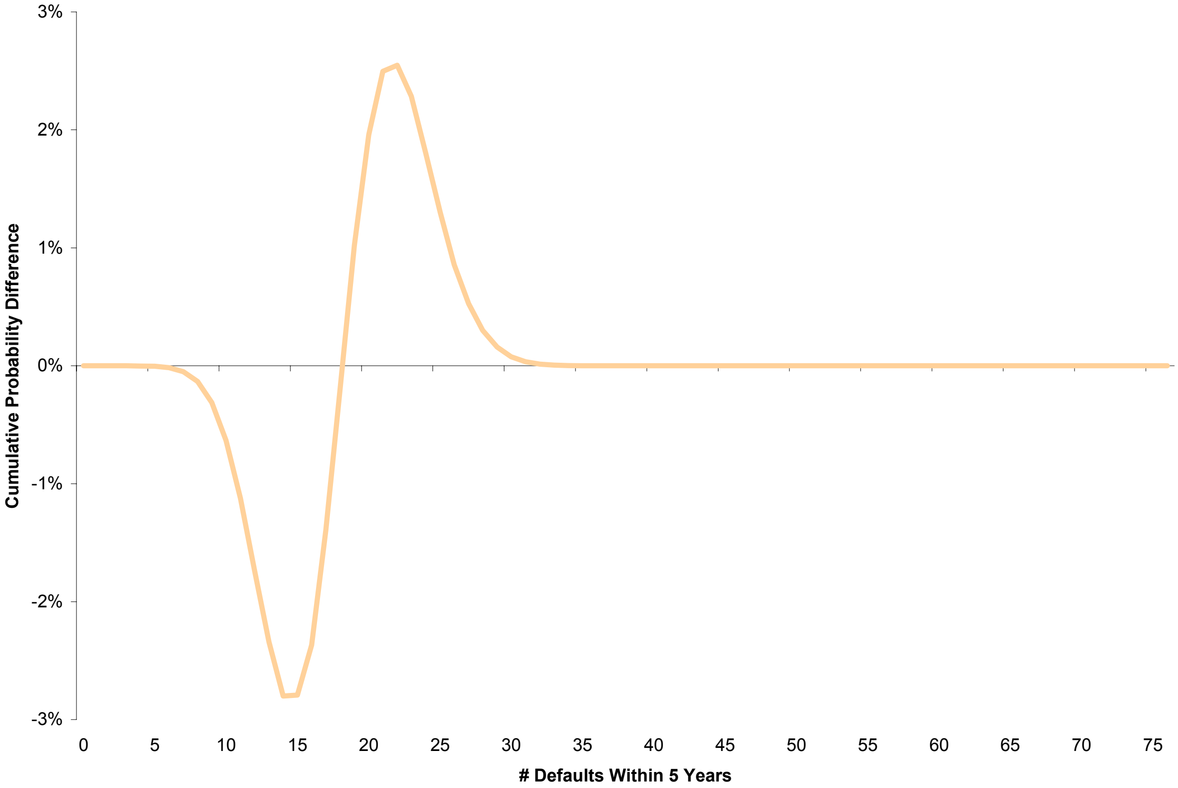


Figure 17: The Individual Cumulative Distribution First Lags, then Leads the Average



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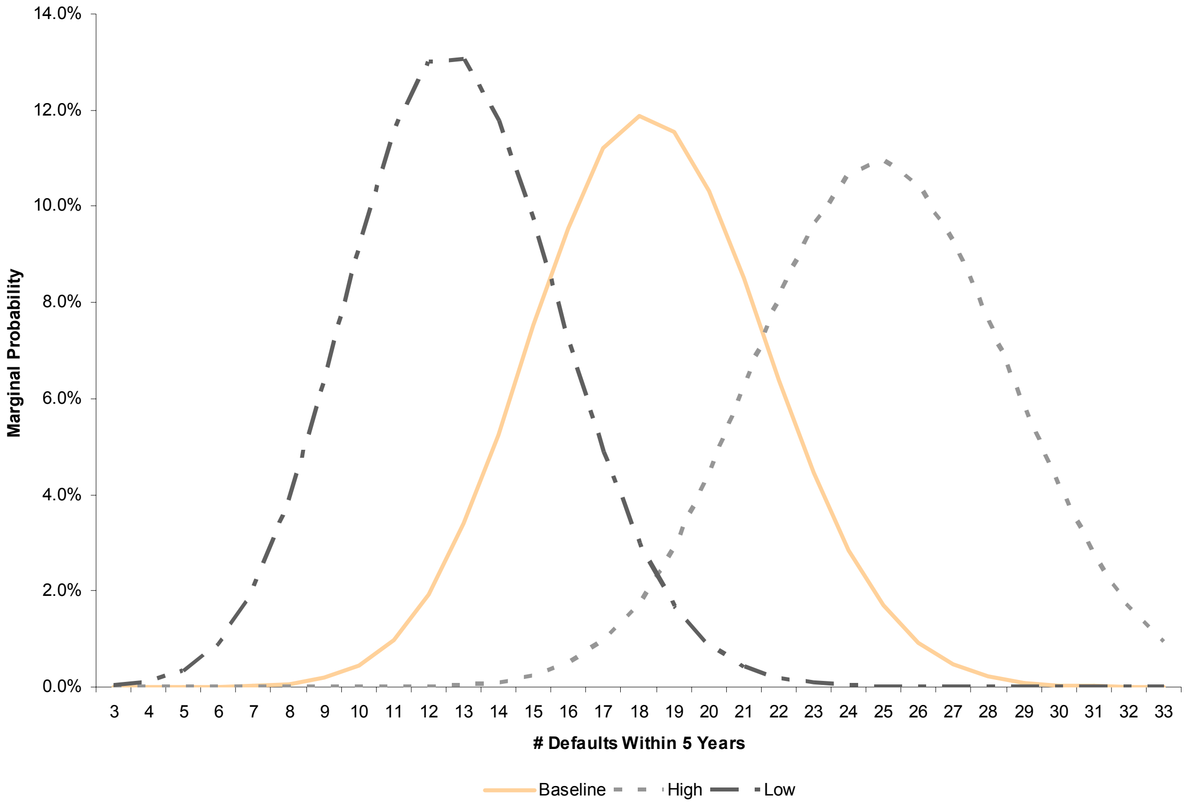
If we ask the question, "what is the probability of observing at least *n* defaults?" for *n* less than 19 we will get a higher probability (a "more conservative" answer) from the individual model. While we always expect to have 18 defaults, the probability that we have at least 15 defaults is 80.2% when considering the issuer-specific probabilities, and only 77.4% when using the portfolio average. Of course, if we ask what is the probability of having at least 21 defaults, the issuer-specific estimate suggests 17.2%, while using the average suggests 19.7%. All we can really say is that the two estimates of portfolio losses are different – we cannot say that one is inherently more conservative than the other.[11] Making use of the issuer-specific probabilities amounts to recognizing that some issuers will almost always default (hence the probability of few losses is very low), but that some others will almost never default (hence the probability of many losses is very low).

Another advantage of the Credit Transition Model is that it links default probabilities to macroeconomic scenarios. We can thus compare portfolio loss distributions across different scenarios. Figure 18 compares the marginal probability distributions under the positive, negative, and baseline economic scenarios.

Figure 18: Comparing Portfolio Losses Under Different Economic Scenarios



If we are able to assign probabilities to the economic scenarios, then we could obtain a probability-weighted estimate of the portfolio loss distribution.

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[11] There is one sense in which using the portfolio average is "conservative:" it is tantamount to discounting the very high and very low individual probability estimates given by the model.

VI Conclusion

Moody's Credit Transition Model can be applied to virtually any question about ratings and default. It produces probabilities of upgrade, downgrade, default and withdrawal for individual issuers, and thus for arbitrary portfolios of issuers. Furthermore, these forecasts can be extended – in a mutually consistent way – to any time horizon. Since the model conditions on the expected future path of the economy, performing sensitivity analysis and scenario testing is straightforward.

To solve any one particular problem – say, the one year default rate for the global speculative-grade universe – other models may perform with greater accuracy. The advantage of the Credit Transition Model is that it is one model which can be consistently applied to essentially any problem of ratings migration, and hence changes in credit quality. And, at least historically, it has done so with great accuracy. Accurately forecasting such physical probabilities can be a key input in pricing models.

The model is uniquely capable of delivering first-passage probabilities across rating boundaries, probabilities of the type needed for portfolios subject to credit rating investment criteria and CDOs. These probabilities can only be crudely approximated (if approximated at all) by using standard transition matrices. To our knowledge, there is currently no other source for such information.

Moody's will begin using the model in its Monthly Default Reports. In fact, many of the exhibits presented above will become regular features of that report. Additionally, Moody's will be offering this model to subscribers in 2008.

References

- Altman, E. (1968). "Financial Ratios, Discrimant Analysis and the Prediction of Corporate Bankruptcy," *The Journal of Finance* 23 (4), 589-609.
- Cantor, R. and D. Hamilton (2007). "Adjusting Corporate Default Rates for Rating Withdrawals," *Journal of Credit Risk*, Summer (forthcoming).
- Fons, J. (1991). "An Approach to Forecasting Default Rates," *Moody's Special Report*, August 1991.
- Fridson, M, Garman, M. and S. Wu (1997). "Real Interest Rates and the Default Rate on High-Yield Bonds," *The Journal of Fixed Income*, September 1997, 29-34.
- Helwege, J and P. Kleiman (1997). "Understanding Aggregate Default Rates on High-Yield Bonds," *The Journal of Fixed Income*, June 1997, 55-61.
- Jónsson, J. and M. Fridson (1996). "Forecasting Default Rates on High-Yield Bonds," *The Journal of Fixed Income*, June 1996, 69-77.
- Keenan, S., Sobehart, J. and D. Hamilton (1999). "Predicting Default Rates: A Forecasting Model for Moody's Issuer-Based Default Rates," *Moody's Special Comment*, August 1999.
- Mann, C. and R. Cantor (2007). "The Performance of Moody's Corporate Bond Ratings: March 2007 Quarterly Update," *Moody's Special Comment*, April 2007.
- Martin, D. (1977). "Early Warning of Bank Failure: A Logit Regression Approach," *Journal of Banking and Finance* 1, 249-276.
- Metz, A. (2007). "A Cyclical Model of Multiple-Horizon Credit Rating Transitions and Default," *Moody's Special Comment*, August 2007.
- Ohlsen, J. (1980). "Financial Ratios and the Probabilistic Prediction of Bankruptcy," *Journal of Accounting Research,* Spring 1980, 109-131.
- Okashima, K. and M. Fridson (2000). "Downgrade/Upgrade Ratio Leads Default Rate," *Journal of Fixed Income*, September 2000, 18-24.

Related Research

- *Moody's Monthly Default Report: July 2007*
- *"A Cyclical* Model of Multiple-Horizon Credit Rating Transitions and Default," *Moody's Special Comment*, August 2007

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Author(s)	**Production Manager**
Albert Metz	William L. Thompson

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