Estimation of Distress Costs Associated with Downgrades Using Regime-Switching Models[1]

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Abstract

We use a unique dataset of bond downgrades from a niche rating company that has been found to be reacting faster to publicly available information than its competitors. Using regime-switching models we propose risk measures to quantify stock return disturbances (distress costs) associated with the timing of downgrades. These risk measures are based on the Capital Asset Pricing Model (CAPM) and use the estimated parameters of the regime-switching models. We observe a noticeable switch from a low-volatility to a high-volatility regime one day before the day of downgrades. On average the volatility in stock returns triples around the time of downgrades, and the stock return process remains in the high-volatility regime for about three days. Using our proposed risk measure we find that stock returns are associated with distress costs of about 22*d% (where ''d'' is the daily market price of risk) over a window of 10 days before and after downgrades. These costs can be further separated between bond-rating companies that are designated by the SEC as nationally recognized to rate debt and those that are not.

1. Introduction

1.1 Motivation

In this paper we use time-series stock return data to estimate costs of distress associated with a selected sample of downgrades. We use a unique dataset of senior unsecured bond ratings from a niche rating company, Egan Jones (EJ), which has been found to be faster than its competitors in releasing ratings changes. Beaver, Shakespeare, and Soliman (2006) find EJ to be one to four months faster than Moody's in releasing a downgrade and up to six months faster in releasing an upgrade. Furthermore Johnson (2004) finds that S&P lags EJ's rating changes especially around the investment-grade boundary.

In our paper we employ regime-switching models to describe the time-series evolution of stock returns around the time of downgrades. We expect that the time period lagging and following downgrades will have some information value and may have significant impact on the dynamics of stock returns. In particular, it may cause a structural change in the stock returns' dynamics. We attempt to capture such structural change in the stock returns' dynamics through regime-switching models. We expect that, around the time of a downgrade, a company's stock returns are more likely to switch from an ''undistressed'' regime to a ''distressed'' regime with lower mean return and higher volatility. The switching between the two regimes is modeled by an unobserved discrete-time, two-state Markov process (Hamilton 1989). In addition, the model allows us to identify exactly the timing (date) of a re-

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gime change through the estimated conditional probability of being in one of the two regimes. Therefore, given the date of a downgrade and the time of the regime switch we can conclude whether downgrades precede or follow changes in regimes. This provides important implications for the lead-lag effect of the downgrades and the regime switching. Finally we propose state-contingent measures to quantify (stock return) costs associated with downgrades.

This paper makes contributions in several aspects. First, we observe a high probability of switching to a distressed regime on the day of the downgrade. Our second contribution is to propose a method to quantify distress costs associated with downgrades using the parameters of a regime-switching model and the estimated daily probabilities of being in each regime. This measure of the cost of distress is based on the Capital Asset Pricing Model (CAPM). In summary, we find that on average the distressed regime has a daily volatility of 6.10%, which is more than three times the volatility of the undistressed regime (1.92%). We find that distress costs on stock returns range from 9.49*d% to 12.91*d% (where ‘‘d’’ is the daily market price of risk) for the 10 days prior to the day of the downgrade. Our estimates are consistent with some prior literature on the information value of bond ratings on stock returns (Wakeman 1981; Hand, Holthausen, and Leftwich 1992; Goh and Ederington 1993, 1999). Additionally we estimate that the conditional duration of the distressed (high-volatility) regime is 3.2 days given a downgrade. Interestingly, EJ seems to be downgrading when the market starts reacting to new information, which potentially allows investors to exploit the remaining window of high volatility.

Section 2 of this paper describes the data selection process. Section 3 sets the theoretical background, develops the hypotheses, explains the methodology, and defines the ‘‘Probability-Volatility’’ (Prob-Vol) measure. Section 4 presents empirical results. Section 5 provides discussions, and Section 6 concludes the paper.

2. DATA AND SAMPLE SELECTION

2.1 Types of Bond-Rating Companies

Bond-rating companies provide opinions about the creditworthiness of debt-issuing companies based on public and private information available. They communicate their opinions through bond ratings that correspond to the probability of default on a rated debt. Bond ratings are updated in the course of time depending on the arrival of new information.

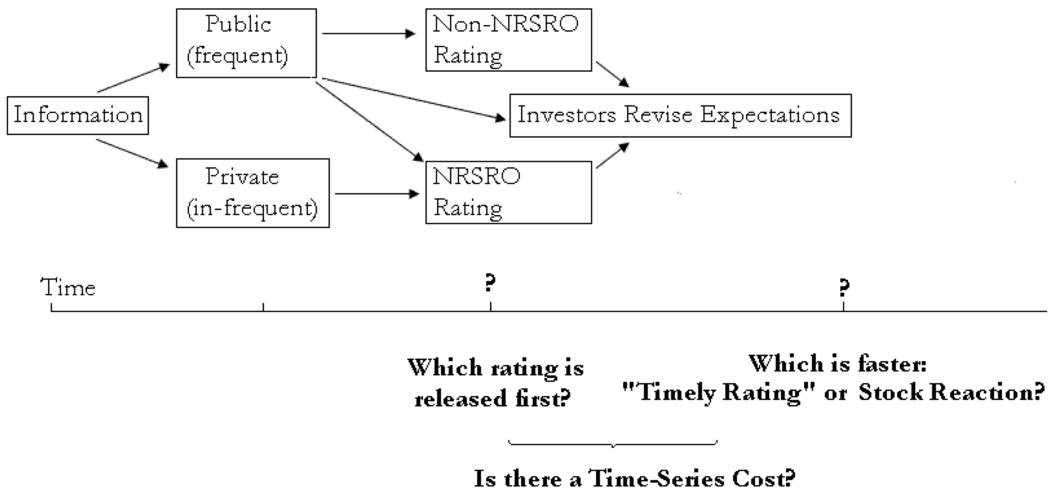
Two main categories of bond-rating companies exist: (a) NRSROs (Nationally Recognized Statistical Rating Organizations), which are solicited (and paid) by debt-issuing companies, and (b) non-NRSROs, which are solicited (and paid) by investors.[2] This separation in the bond-rating market gives NRSROs the comparative advantage of private information as they meet with debt-issuing companies to get a better understanding of companies' internal operations. On the other hand non-NRSROs depend only on publicly available information to form their opinions (ratings) (Fig. 1). Additionally, differences in the compensation structure of bond-rating companies could be creating a misalignment of incentives with respect to the timeliness and accuracy of ratings.

Timeliness is important in rating changes as it gives investors early warning about potential gains or losses from new information release. Two recent scandals that highlighted the importance of timely downgrades were Enron and WorldCom. In both cases EJ, a non-NRSRO, provided early warning to investors much earlier than S&P and Moody's (both of them are NRSROs).[3] However, changing ratings too often might backfire on the credibility of bond-rating companies. This is because costs that may occur from wrongly downgrading a company are higher than gains from wrongly upgrading another similar company (Watts 1977).

[2] The U.S. Securities and Exchange Commission (SEC) requires debt-issuing companies to get rated from one of the five NRSROs: A.M. Best Company, Inc., Dominion Bond Rating Service Ltd., Fitch, Inc., Moody's Investors Service, and the Standard & Poor's Division of the McGraw Hill Companies Inc. Even though there are many smaller rating companies, the SEC only uses the ratings provided by NRSROs. There is therefore a barrier to entry into the bond-rating industry as the NRSROs have guaranteed business, while smaller companies depend on proceeds from investors to evaluate the creditworthiness of debt-issuing companies.

[3] For example, in the case of Enron, EJ downgraded to non-investment grade on June 27, 2001, while S&P and Moody's waited until four days before Enron declared bankruptcy (December 3, 2001).

Figure 1
Timing of Information Flow, Bond Ratings, and Stock Reactions



Accuracy (consistency) among rating agencies is also important for investors. This is because investors want to be able to form a consistent opinion about the credit worthiness of debt-issuing companies by looking at ratings published by different rating companies. However, accuracy among ratings is not always the case as there is usually asymmetric information between NRSROs and non-NRSROs, and there might be different incentives between the two agencies (Fig. 1).

Accuracy and timeliness are important factors in our sample selection process.

2.2 Sample Selection: Timely Downgrades

Beaver, Shakespeare, and Soliman (2006, hereafter BSS) compare rating changes by Moody's (NRSRO) and EJ (non-NRSRO). They find that EJ is one to four months faster in releasing a downgrade than Moody's. BSS chose EJ to be a representative non-NRSRO for the following reasons: (a) EJ rates companies across different industries, (b) they have been cited repeatedly for their fast responses to market signals, (c) they have participated in the SEC hearings regarding competitiveness in the bond-rating markets, and (d) they are one of most positively publicized non-NRSRO's companies.

We felt that BSS's thorough analysis on the timeliness between EJ and Moody's would be a good starting point for our analysis. Therefore we asked BSS if we could have access to their dataset. We are grateful and indebted for their willingness to share their data with us. Given the time lag they establish between the two rating companies, we expect that there will be some information value (distress cost) associated with the earliest rating (downgrade). Therefore we choose a set of *timely* downgrades to quantify this cost.

We define a *timely* downgrade as the earliest downgrade between Moody's and EJ to the same relative rating. Ratings from EJ and Moody's are translated to a common numeric scale following the Fixed Income Securities Database (FISD) and BSS (Table 1). Our data selection process included careful collection of observations that satisfied the following criteria: (a) a downgrade by one rating company, (b) later verified by the second company, (c) to the same eventual rating. We do not include downgrades that are later reversed or those that are not of the same rating. A faster downgrade by EJ would imply a timelier response than Moody's to new public information. On the other hand, a faster downgrade by Moody's could imply the release of private information or a late response of EJ to public information. Furthermore, given the lead time between EJ and S&P (Johnson 2004) we matched observations from our final sample with rating changes in FISD from other NRSROs. This allowed us to verify that no

Table 1
Moody's and EJ Rate on a Comparable Scale

Moody's Scale	Egan Jones' Scale	Numerical Scale	Moody's Scale	Egan Jones' Scale	Numerical Scale
Aaa	AAA	1	Ba2	BB	12
Aa1	AA+	2	Ba3	BB−	13
Aa2	AA	3	B1	B+	14
Aa3	AA−	4	B2	B	15
A1	A+	5	B3	B−	16
A2	A	6	Caa1	CCC+	17
A3	A−	7	Caa2	CCC+	18
Baa1	BBB+	8	Caa3	CCC−	19
Baa2	BBB+	9	Ca	CC	20
Baa3[a]	***BBB−***	***10***	C	C	21
Ba1	BB+	11		D	22

[a] Lowest Investment-Grade Rating.

additional noise was added to our estimation window.[4]

2.3 Final Sample

Our final dataset includes 235 observations for which a downgrade by EJ was later confirmed by Moody's and vice versa. Our next step was to match the debt issuing numbers (CUSIP)[5] in our sample with the database of the Center of Research in Security Prices (CRSP). This allowed us to collect the issuing company's daily stock prices for a period of at least one year before and after the time of downgrade. Downgrades in our sample took place between January 1997 and July 2002. Stock prices were adjusted for stock splits and dividends.

The single most important element of our dataset was the actual date of the earliest downgrade. We define ''noise'' as a rating change in a window of three months before and after the date of the earliest downgrade. The 235 observations were heterogeneous with respect to the noise from other rating actions before and after the earliest downgrade. Therefore we chose those observations that had no other downgrades or upgrades 92 days (three months) before and after the earliest downgrade. We chose a window of three months since companies typically announce earnings every quarter.

This reduced our sample from 235 to 90 observations, which we describe with respect to their rating and noise (in days) from other rating actions around the earliest downgrade (Table 2). EJ downgraded first in 58 out of 90 observations, with an average rating of 10 (lowest investment-grade bond), which were confirmed by Moody's about 329 days later. The average earliest downgrade by Moody's was noninvestment grade (11.38), which was confirmed by EJ about 396 days later. ''Noise windows'' after the earliest EJ and Moody's ratings were 278 and 371 days, respectively, while noise windows before the earliest downgrades were 391 and 266, respectively.

3. MODEL, HYPOTHESES, AND METHODOLOGY

3.1 Theoretical Model: Markov Switching between Two Lognormal Distributions

Regime-switching models were first introduced by Hamilton (1989) when he proposed using a time-series model with parameters driven by a discrete-time Markov chain process with two independent regimes to model data that had large and discrete shifts in values from previous periods. Hamilton improved the Goldfeld and Quandt (1973) switching regression (underlying Markov chain) by allowing the existence of several regimes and examining different autoregressive models as can-

[4] We looked up ratings from Fitch Ratings, Standard and Poor's, and Duff and Phelps in a 100-day window before the event days in our final sample of timely downgrades. There were no rating changes from other NRSRO's to the same rating in the 100-day window before.

[5] CUSIP numbers are issued by the Committee on Uniform Securities Identification Procedures. This number identifies a company and a specific debt issue.

Table 2
Other Rating Changes Close to a Timely Downgrade

Descriptive Statistics	Egan Jones Downgrades First: Noise Before	Noise After	Confirmed	Downgraded to
Mean	390.97	277.90	329.26	10.00
Standard error	47.95	27.38	29.17	0.32
Median	299.00	213.50	280.00	10.00
Standard deviation	287.69	208.51	222.17	2.43
Kurtosis	0.29	3.86	2.64	(0.89)
Skewness	1.07	1.91	1.58	0.09
Count	36[a]	58	58	58
Descriptive Statistics	**Moody's Downgrades First: Noise Before**	**Noise After**	**Confirmed**	**Downgraded to**
Mean	266.28	371.38	396.03	11.38
Standard error	48.38	40.51	40.00	0.48
Median	166.50	316.50	365.00	11.50
Standard deviation	205.27	229.13	226.26	2.73
Kurtosis	3.27	1.62	1.21	(1.18)
Skewness	1.88	1.40	1.22	(0.06)
Count	18[b]	32	32	32

[a] 22 out of 58 timely downgrades by EJ had no noise before.
[b] 14 out of 32 timely downgrades by Moody's had no noise before.

didate models for the underlying regimes (Hamilton and Susmel 1994). His model found later applications in Bayesian Markov Chain Monte Carlo estimations (Harris 1997) and pricing of options through lattices (Bollen 1998), among numerous other applications. Finally, in an important contribution Hardy (2001) derived the probability function of the process, compared insurance-based risk measures with other models, and explored implications on maturity guarantees of equity-linked insurance. We follow Hardy's (2001) notation and direct the reader to her paper for all derivations and useful results of the regime-switching process.

We assume that a stock price follows a continuous-time diffusion process that switches between two regimes: an ''undistressed'' and a ''distressed'' regime (Fig. 2). State 1 and State 2 represent undistressed and distressed regimes. Consider a Markov Chain with two independent states and transition probability matrix:

$$P = \begin{bmatrix} p_{1,1} & p_{1,2} \\ p_{2,1} & p_{2,2} \end{bmatrix}, \tag{3.1}$$

where $p_{i,j} = \Pr[\rho_{t+1} = j | \rho_t = i]$, is the probability that the daily process (stock returns) will switch from regime i at time t to regime j at time $t + 1$, ρ_t is the regime on day t, $p_{1,2} = 1 - p_{1,1}$, and $p_{2,1} = 1 - p_{2,2}$. Let $Y_t = \log(S_{t+1}/S_t)$ be the daily log-return of a stock at day t. The process that characterizes Y_t is assumed to switch randomly between two regimes in an unobserved Markov process. Let ${}^1Y_t$ and ${}^2Y_t$ denote the undistressed and distressed regimes, respectively. The stock return process can be in one of the two regimes with some probability governed by a Markov switching process, ρ_t (Fig. 3). More specifically the process can be summarized by

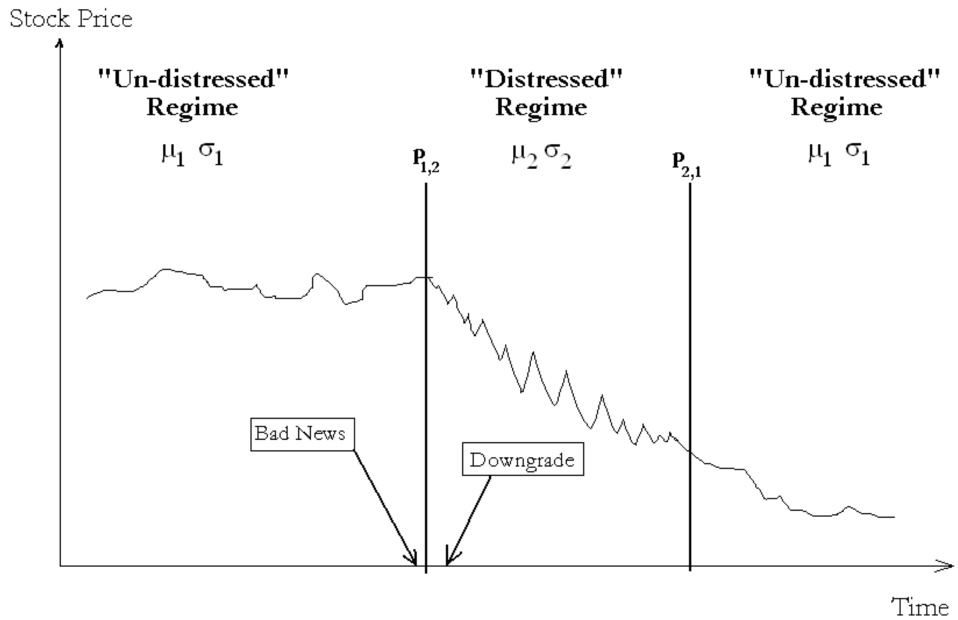
$$Y_t = \begin{cases} {}^1Y_t = \mu_1 t + \sigma_1 W_t, & \text{if } \rho_t = 1 \\ {}^2Y_t = \mu_2 t + \sigma_2 W_t, & \text{otherwise.} \end{cases} \tag{3.2}$$

${}^{\rho_t}Y_t$ characterizes the process in regime ρ_t between time periods $[t, t + 1)$ where $\rho_t = 1, 2$. ${}^{\rho_t}Y_t$ implies a lognormal distribution with mean μ_{ρ_t} and volatility σ_{ρ_t}. W_t is a standard Brownian motion. The final model (RSLN2) includes two lognormal regimes, which are conditionally independent and are overall characterized by six parameters: $\Theta = \{\mu_1, \mu_2, \sigma_1, \sigma_2, p_{1,2}, p_{2,1}\}$.

Around the event of a timely downgrade, we expect stock returns to switch between two Brownian motions with different drifts and volatilities (eq. 3.1). Consequently, if stock returns follow an ''undistressed'' regime before and a ''distressed'' regime after the release of bad news, then stock returns are expected to switch between these two regimes at some point around which the new information is released.

There are several aspects of the regime-switching model that make it suitable for this

Figure 2
Illustration of a Possible Path in Stock Price around a Downgrade Event

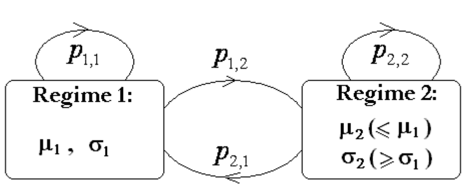


analysis. First, if there is indeed a change in regime, maximum likelihood estimation of the model will reveal the time and persistence of a distressed regime through the daily probability of being in regime 2. Furthermore, differences in the parameters (mean and volatility) of the two regimes will allow us to test our hypotheses and to quantify costs associated with timely downgrades.

3.2 Hypotheses

Suppose that a company is in an ''undistressed'' regime before and in a ''distressed'' regime after bad news are incorporated in the stock price. This would imply a lower mean return for the ''distressed'' regime relative to the mean of the ''undistressed'' regime:

Figure 3
Regime-Switching Model around a Bond Downgrade Event



Hypothesis 1: *Given a regime change around the time of a downgrade, the mean of the new (distressed) regime will be less than or equal to the mean of the old (undistressed) regime.*

Furthermore, we expect that a negative event will introduce uncertainty to the underlying company, therefore increasing volatility in its stock returns:

Hypothesis 2: *Given a regime change around the time of a downgrade, the new (distressed) regime will have higher volatility than the prior (undistressed) regime.*

The beauty of the regime-switching model is that it can pick the time of a change in regime through the maximum likelihood estimation. This is directly observable through the estimated daily probabilities of being in either the distressed or undistressed regime. Therefore, whether a rating responds to public information, or whether it provides new information to the market, the impact (if any) on the company's stock price will be observed through a change in regime at a point picked by the model. Furthermore, if downgrades are timely and respond quickly to new public information, then the timing of the regime change should happen close to the downgrade date. This would be the case for non-NRSROs as their business model is built around fast response to public information:

Hypothesis 3: *Timely downgrades from a non-NRSRO (reflect public information) will take place at the time of a regime switch or afterwards.*

In the case of NRSROs, timely downgrades imply either the release of private information or a late response by the non-NRSRO. Therefore it is uncertain when the regime switching will take place. For example, if NRSROs are releasing new private information we expect to see a regime switch in stock returns at the same time or after downgrades. This would signal a market reaction to new information released by the NRSRO. On the other hand if NRSROs are simply reacting to new public information (that the non-NRSRO has missed), then we would expect to see the regime switch before or at the same time as the downgrade. As a result it is not clear at this point which effect will be stronger.

The timing, persistency, and likelihood of being in a distressed regime imply distress costs to investors. To quantify such distress costs we propose a measure that combines estimates of the mean, volatility, and daily likelihood of where the process is on any given day. Estimates of this measure are obtained separately for the two rating companies for periods preceding and following timely downgrades. Our proposed measure is derived below.

3.3 Methodology

3.3.1 Maximum Likelihood Estimation and Robustness Tests

We follow Hardy (2001) to maximize the likelihood function and obtain parameter estimates for the regime-switching process. The log-likelihood function is given by

$$\log[L(\Theta)] = \sum_{1}^{n} \log[f(y_t|\Theta, y_1, y_2, y_3, \ldots, y_{t-1})],$$
$$t = 1, 2, \ldots, n, \tag{3.3}$$

where n is 201 (100 days before and after the event day), f is the probability density function of y_t, and $\Theta = \{\mu_1, \mu_2, \sigma_1, \sigma_2, p_{1,2}, p_{2,1}\}$ is the set of parameters to be estimated. μ_i is the mean and σ_i is the volatility of regime i, and $p_{i,j}$ is the transition probability from regime i to j. The maximum likelihood estimation is done recursively by using several starting values for Θ. For each of the 90 companies we choose $\bar{\Theta}$ (estimated parameters) that gives the highest log-likelihood value.

As a first robustness check we vary the number of days before and after the event date from 201 down to 161 and up to 241, respectively. Even though there are some changes in $\bar{\Theta}$, the timing of the regime change is not affected. Therefore we decided to stay with the 100-day window because of the tradeoff between additional observations and noise in our estimation window from additional changes in ratings.

Furthermore, we test the hypothesis of *no* regime switching taking place by fitting a single log-normal distribution on the log of daily returns. We compare goodness-of-fit tests[6] between the regime-switching model of two lognormals (RSLN2) and the single lognormal. The results are overwhelmingly in favor of the RSLN2.

As another important robustness check, also following Hardy (2001), we fit the same data to a regime-switching model between two first-order autoregressive processes, RSAR(1). The likelihood ratio test rejects RSAR(1) in 84 out of the 90 cases, as the additional two parameters required by this model do not justify an improvement on the log-likelihood value. Therefore, to keep a consistent story, we proceed with the results from the RSLN2.

An important intermediate part of the process is the estimation of daily probability of being in regime i at day t given the observations in the previous t days. For the rest of this paper we let q_t represent the daily probability of being in regime 2 (distressed regime) on day t:

$$q_t = p(\rho_t = 2|y_t, y_{t-1}, \ldots, y_1, \Theta), \tag{3.4}$$

$$(1 - q_t) = p(\rho_t = 1|y_t, y_{t-1}, \ldots, y_1, \Theta). \tag{3.5}$$

Consequently $(1 - q_t)$ would be the respective probability for regime 1. In other words, on any given day, the stock return process will be in either a distressed or undistressed state conditional on where the process was in the previous period.

[6] Likelihood Ratio Test, Akaike Information Criterion, Schwartz Bayes Criterion.

Here q_t is by itself a measure of the likelihood of being under distress; therefore we use it for the estimation of the implied daily distress cost.

3.3.2 Proposed Measure to Quantify Time-Series Distress Costs

We propose a general measure to capture (stock return) distress costs associated with downgrades. This measure is based on the principles of the capital asset pricing model (CAPM), uses some of the estimated parameters of RSLN2 (μ_1, μ_2, σ_1, σ_2), and uses q_t as well.

The Capital Asset Pricing model states that the return investors expect from investing in a security, A, should equal the risk-free rate plus a risk premium: $r_A = r_f + \beta_A(r_m - r_f)$, where r_A is the return of the security, r_f is the risk-free rate, r_m is the market (or index) return, and $\beta_A = \mathrm{cov}(r_A, r_m)/\sigma_m^2$, where σ_m is the market volatility. CAPM implies that there should be a *market price of risk*, λ_A, that instantaneously satisfies

$$\lambda_A = (r_A - r_f)/\sigma_A. \tag{3.6}$$

The market price of risk per annum (λ_A) is related to daily market price of risk (''d'') according to a square-root rule:

$$\lambda_A = \sqrt{252} \times \mathrm{d}$$

where we assume there are 252 trading days in a year.

We make the standard econometric assumption that λ_A is constant over our estimation period. This implies that the investor has constant relative risk aversion and that her risk preferences do not change over the estimation period. Therefore the market price of risk can be estimated historically based on an industry or company specific index (i.e., its own stock price). This would imply that there is a market price of risk that would risk-neutralize returns to equal the risk-free rate.[7] For simplicity, we assume that the daily market price of risk is a constant ''d.'' In fact, a reliable estimate, even a constant λ_A, is elusive because it is sensitive to the period analyzed and may differ significantly when estimated retrospectively or prospectively. Using S&P500 index daily price data from January 3, 1950 to December 29, 2006, assuming per annum risk free rate of 6% our estimated λ_A is 0.21, which gives a constant ''d'' of 0.0133.

In the context of our paper and hypotheses stated we expect the distressed regime to have a lower mean and higher volatility than the undistressed regime. Therefore we propose using a daily measure to capture costs associated with downgrades as a function of the differential in the parameters of the two regimes and the probability of being in each regime every day. Let $\mu_1^* = \mu_1 - \mathrm{d} \times (\sigma_1)$ and $\mu_2^* = \mu_2 - \mathrm{d} \times (\sigma_2)$ be the risk-adjusted returns in each regime using the security's market price of risk. Then the daily cost of being in the distressed regime would be equal to

$$q_t \times (\mu_1^* - \mu_2^*) = q_t \times (\mu_1 - \mu_2 + \mathrm{d}(\sigma_2 - \sigma_1)), \tag{3.7}$$

where q_t is the probability of the process being in the distressed regime on day t, $\mu_1 > \mu_2$, and $\sigma_2 > \sigma_1$. If the process stays in the undistressed regime then no costs will be incurred. Therefore an m-day cost associated with a negative event (downgrade, bad news, a loss of some kind) would be equal to

$$\sum_{t=1}^{m} [q_t \times (\mu_1^* - \mu_2^*)]. \tag{3.8}$$

4. EMPIRICAL RESULTS

For each company we obtain a set of parameters $\bar{\Theta} = \{\mu_1, \mu_2, \sigma_1, \sigma_2, p_{1,2}, p_{2,1}\}$ that maximize the log-likelihood function and q_t, where $1 < t < 201$. For our estimation we allow the model to choose the values of μ_i, σ_i for each regime with no restrictions. The top panel of Table 3 reports the descriptive statistics across the 90 companies. The mean of the undistressed regime ($\mu_1 = -0.20\%$) seems to be slightly higher than the mean of the distressed regime ($\mu_2 = -1.29\%$) and in favor of hypothesis 1. Furthermore, there seems to be a significant difference between the

[7] We could even use the parameters of the RSLN2 to obtain an estimate of λ_A as given by Hardy (2001): The price of a security n days into the future, S_n, in a regime-switching model between two lognormal distributions can be described by $S_n|R \approx \mathit{Lognormal}\ (r^*(R), \sigma^*(R))$, where R is the number of days in regime 1, $r^*(R) = \mu_1(R) + \mu_2(n - R)$, and $\sigma^*(R) = \sqrt{\sigma_1^2(R) + \sigma_2^2(n - R)}$. Alternatively one can assume that the lambda can be derived from the undistressed regime since the distressed regime is only temporary.

Table 3

Descriptive Statistics for RSLN2's Parameters

RSLN2	Parameter	Mean	N	Std. Deviation	Std. Error Mean
(a) Different means	μ_1	−0.20%	90	0.34%	0.04%
	μ_2	−1.29	90	6.14	0.65
	σ_1	1.97	90	0.95	0.10
	σ_2	5.47	90	3.60	0.38
	P_{12}	14.81	90	17.86	1.88
	P_{21}	33.32	90	27.24	2.87
(b) Equal means	μ_1	−0.15	90	0.27	0.03
	μ_2	−0.15	90	0.27	0.03
	σ_1	1.92	90	0.85	0.09
	σ_2	6.10	90	4.31	0.45
	p_{12}	15.21	90	18.60	1.96
	p_{21}	30.97	90	26.53	2.80

Table 4a

Testing Hypothesis 1 and 2: RSLN2 with Different Means and Different Volatilities

Testing	Test	Null Hypothesis	Mean	Std. Deviation	*t*-Value	DF	Sig. (1-tailed)	Sig. (2-tailed)
Hyp. 1	*t*-test	$\mu_1 \leq \mu_2$	1.084%	6.138%	1.6754757	89	0.0486755	0.0973510
Hyp. 2	*t*-test	$\sigma_1 \leq \sigma_2$	3.495%	3.232	10.2597302	89	0.0000000	n/a
Other	*t*-test	$p_{21} \leq p_{12}$	18.505%	33.843	5.1873918	89	0.0000007	n/a

Table 4b

Testing Hypothesis 2: RSLN2 with Same Means and Different Volatilities

Testing	Test	Null Hypothesis	Mean	Std. Deviation	*t*-Value	DF	Sig. (1-tailed)	Sig. (2-tailed)
Hyp. 2	*t*-test	$\sigma_1 \geq \sigma_2$	4.179%	3.708%	10.6916671	89	0.0000000	n/a
Other	*t*-test	$p_{21} \leq p_{12}$	15.760%	34.420	4.3437811	89	0.0000185	n/a

volatility of the distressed ($\sigma_2 = 5.47\%$) and undistressed regime ($\sigma_1 = 1.97\%$).

4.1 Strong Evidence for Different Volatilities: Not Sufficient Evidence for Different Means

However, the one-tailed *t*-test across the 90 companies (Table 4a) shows that there is insufficient evidence in support of hypothesis 1 (H1: $\mu_1 > \mu_2$). Even though the average difference between μ_1 and μ_2 is positive (1.08%), the result is not statistically significant at the 1% significance level.[8] There is, on the other hand, strong evidence in support of hypothesis 2 (H2: $\sigma_2 > \sigma_1$). The volatility of the distressed regime, σ_2, is found to be significantly higher by about 3.50% than the volatility of the undistressed regime, σ_1, at the 1% significance level.[9]

Given that the means are not significantly different, we decided to rerun the RSLN2 model by setting the two means equal to each other ($\mu_1 = \mu_2$) and allowing the volatility to vary.[10] This restriction forces the volatility parameter in the two regimes to absorb variations in stock returns that were earlier absorbed in the mean differential. Likelihood ratio tests between the two models are in support of the equal-mean model. More specif-

[8] We tested hypothesis 1 under the RSAR model. There is still not enough evidence to support the hypothesis (*p*-value < 0.1123).

[9] If the means were statistically significant, a rough estimate of the maximum daily cost of distress associated with downgrades (as defined in Equation 3.7) would be [1.08% + d(3.50%)] multiplied by the probability of being in Regime 2.

[10] A two-tailed *t*-test was performed to test the equality of the means, and we found that the means are not statistically significant from each other (Table 4a: last column, first row).

ically, for 89 out of the 90 companies the additional parameter (from allowing the means to vary) did not justify the increase in the log-likelihood value.[11]

The second panel of Table 3 reports descriptive statistics for parameter estimates of the RSLN2 with equal means. We find that the mean for both regimes is now −0.15% (s.e. 0.03%) and that the difference between volatilities has widened compared to the different-mean model. The volatility of the distressed regime, σ_2, has increased to 6.10%, while the respective volatility of the undistressed regime, σ_1, has decreased slightly (1.92%). The one-tailed *t*-test results (Table 4b) show strong support for hypothesis 2 again, with an average difference in volatility between the two regimes of 4.18% (s.e. 0.39%). We also report differences of the transition probabilities between the two regimes. The probability of switching from the undistressed to the distressed regime is found to be significantly smaller by 15.76% (s.e. 3.63%) than the probability of switching from the distressed to the undistressed regime ($p_{2,1} > p_{1,2}$). This reveals the asymmetry of the switching from one regime to the other. Given the results of Table 4b and 3b we can now calculate transition probability matrix for our sample:

$$P = \begin{bmatrix} p_{1,1} & p_{1,2} \\ p_{2,1} & p_{2,2} \end{bmatrix} = \begin{bmatrix} 0.8479 & 0.1521 \\ 0.3097 & 0.6903 \end{bmatrix},$$

where off-diagonal probabilities are significantly different. In other words, given that the process is in regime 1, it will stay there with a probability of about 85%, while given that the process is in regime 2, then it will switch to the undistressed regime with a probability of about 31%. The estimated transition probabilities imply stationary probabilities of $\pi_1 = p_{21}/(p_{21} + p_{12}) = 67.06\%$ and $\pi_2 = 32.94\%$. These give the probability of being in each regime in the long run.

4.2 Expected Duration in Each Regime

Another interesting result we obtain from the transition probability matrix is the expected duration in regime *i*, conditional on being in that regime. For example, given the process is in the distressed regime then the expected time of remaining in the distressed regime is

$$\sum_{c=1}^{201} c(p_{22})^{c-1}(1 - p_{22}) \approx \sum_{c=1}^{\infty} c(p_{22})^{c-1}(1 - p_{22}) \approx (1 - p_{22})^{-1}. \qquad (4.1)$$

Therefore conditional on entering the distressed regime the stock return process is expected to remain there for an average of 3.2 days.[12] Estimating the result numerically over the 201 days or taking the limit produces almost identical estimates. This is consistent with later results where we estimate the expected "future lifetime" of the distressed regime following the event date (Section 4.4).

4.3 Timing of Downgrades and Regime Switching

Now we look into the timing of regime change and how they compare to the event date. In Figure 4 we show the average probability of being in regime 1 across the 90 companies, where day "101" marks the event date. The line on top shows the average probability from the original model ($\mu_1 \neq \mu_2$; $\sigma_1 \neq \sigma_2$), while the lower line shows the estimation under the revised model ($\mu_1 = \mu_2$; $\sigma_1 \neq \sigma_2$). As we can see, the daily probability of being in each regime is consistent between the two models. The better model ($\mu_1 = \mu_2$; $\sigma_1 \neq \sigma_2$; based on the likelihood ratio test) implies an overall higher probability of being in the distressed regime.

In Figure 4 it is evident that across all ratings there is a noticeable decrease in the probability of being in the low-volatility (undistressed) regime that begins one day before the downgrade. The spike on the figure suggests that our sample downgrades respond quickly to market information. We can also notice a downward (upward) trend in the probability of being in the undistressed (distressed) regime starting about 50 days before the event date.

To test hypothesis 3 we have to look at the timing of regime switching separately for companies downgraded by EJ and Moody's. Figure 5

[11] The one company that seems to favor a difference in the means has $p < 0.0087$ in the LR test.

[12] Standard errors of the transition probabilities imply an expected duration that ranges between 2.96 and 3.55 days.

Figure 4
Average Probability of Undistressed Regime (Downgrade at t = 101)

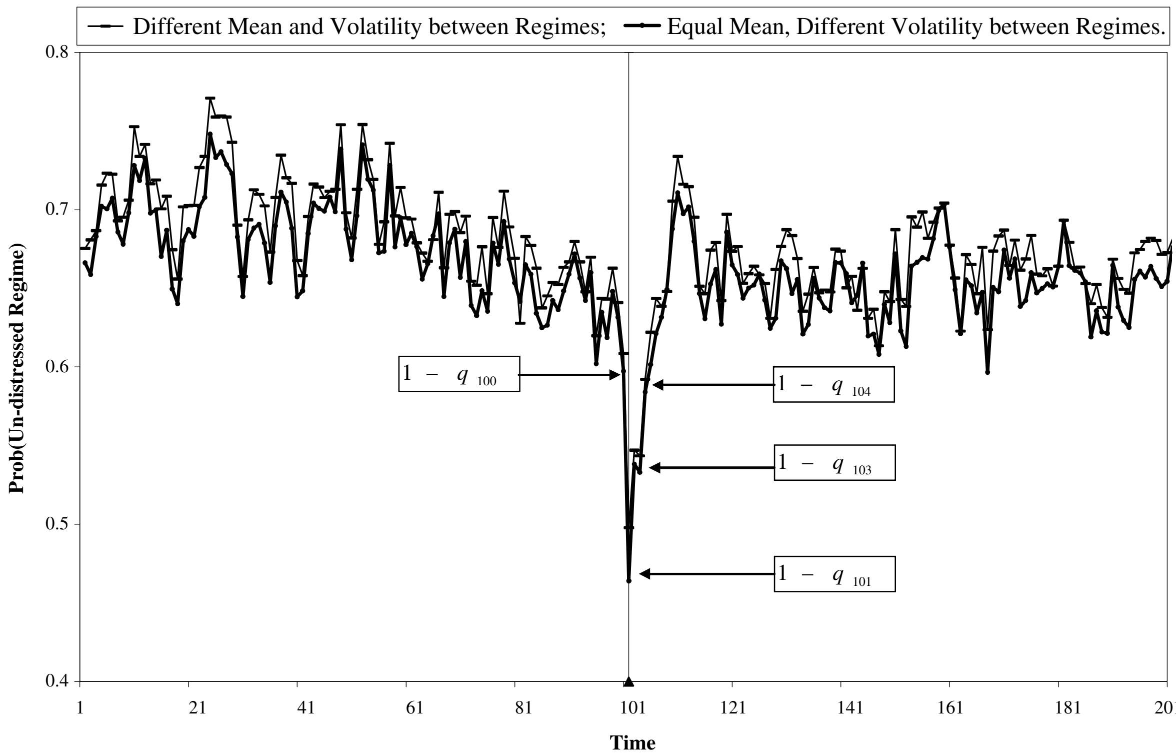


Figure 5
Average Pr(Undistressed Regime) by Rating Company

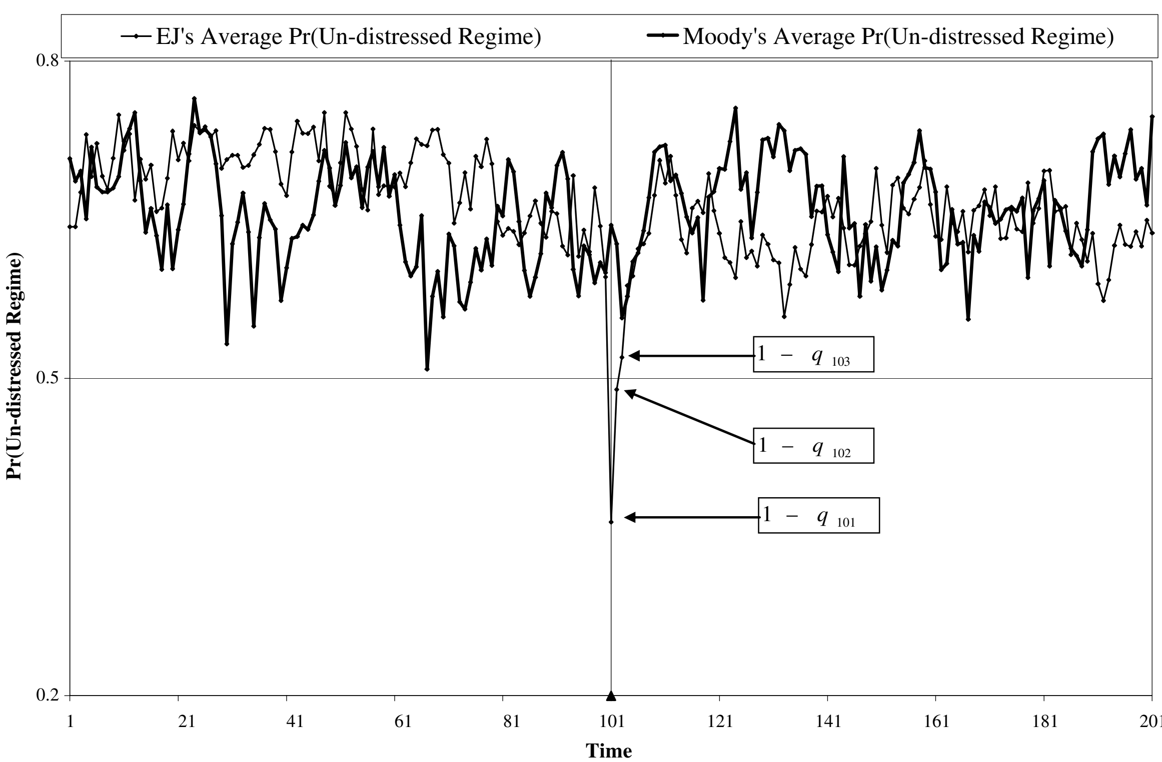
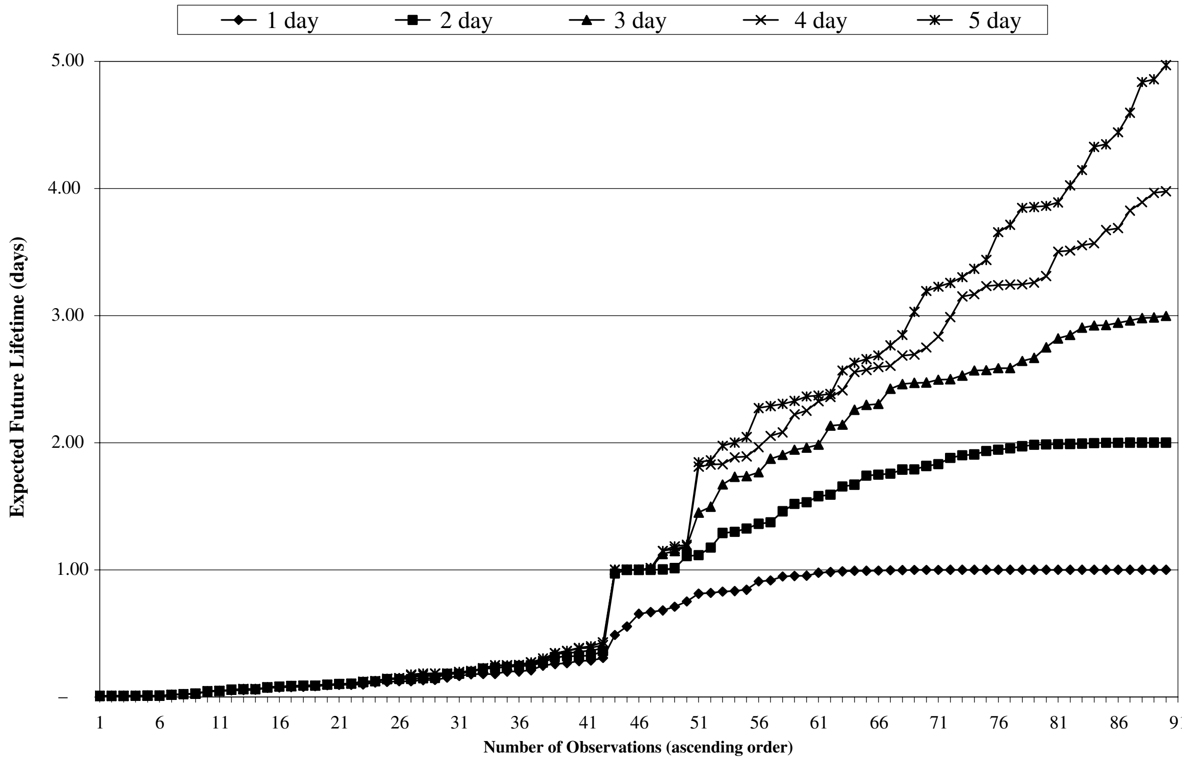


Figure 6
N-day Curtate "Lifetime" Starting at Event Day



shows that EJ is driving the results shown in Figure 4 as they are downgrading on the day that the market is experiencing the highest volatility. This is evidence in support of hypothesis 3 because EJ (non-NRSRO) is downgrading one day after the market shows a likelihood of switching to the distressed regime.[13] In the case of Moody's, however, the process seems to be random with no distinguishable changes in regime.

In summary, even though the process cannot be clearly classified as being in regime 1 or 2, we notice that there is a *tendency* for the process to lean toward the distressed regime around the time of the timely downgrade (t = 101). This *tendency* begins one day before the downgrade (t = 100) and lasts about five days (until t = 104; Fig. 4). We also notice that EJ seems to be downgrading on the day that stock returns experience the highest spike in the probability of being in the distressed regime (Fig. 5). This potentially leaves investors a short window to exploit the tendency of stock returns to stay in the high-volatility regime (the two days following the day of downgrade). We defer a detailed discussion of the results to Section 5.

4.4 Persistence

The next question we investigate is persistence of the high volatility regime. We calculate indicators of the expected duration of regime 2 based on sample's average q_t. The first indicator we examine is the n-day, discrete, future duration of the distressed regime starting at time t. We denote that by $e_{t:\overline{n}|}$:

$$e_{t:\overline{n}|} = \sum_{s=1}^{n} s \times {}_sq_t \times (1 - q_{t+s}), \qquad (4.2)$$

where ${}_sq_t$ is the probability that the process in regime 2 at time t will stay in regime 2 over the next s days. We provide plots for $n \in [1, 5]$ in Figure 6 in ascending order. A spike is observed for about half the sample, which is expected given

[13] The independent samples' t-test on $q_{t=101}$ between the two companies shows EJ to have a higher probability by 28.0% ($p < 0.002$).

Table 5a
Descriptive Statistics for Expected Duration of Distressed Regime (Days)

Period	Rating Comp.	*N*	Mean	Std. Dev.	Std. Error	95% Conf. Interval for Mean		Min.	Max.
						Lower Bound	Upper Bound		
1 day	EJ first	58	0.635703	0.41	0.05	0.53	0.74	0.01	1.00
	Moody's first	32	0.355271	0.38	0.07	0.22	0.49	0.01	1.00
	Total	90	0.535994	0.42	0.04	0.45	0.62	0.01	1.00
2 days	EJ first	58	1.079407	0.79	0.10	0.87	1.29	0.01	2.00
	Moody's first	32	0.626586	0.75	0.13	0.35	0.90	0.01	2.00
	Total	90	0.918404	0.80	0.08	0.75	1.09	0.01	2.00
3 days	EJ first	58	1.41698	1.13	0.15	1.12	1.71	0.01	2.98
	Moody's first	32	0.842132	1.06	0.19	0.46	1.22	0.01	3.00
	Total	90	1.212589	1.13	0.12	0.98	1.45	0.01	3.00
4 days	EJ first	58	1.649979	1.39	0.18	1.28	2.02	0.01	3.98
	Moody's first	32	1.005313	1.30	0.23	0.54	1.48	0.01	3.57
	Total	90	1.420764	1.39	0.15	1.13	1.71	0.01	3.98
5 days	EJ first	58	1.825408	1.62	0.21	1.40	2.25	0.01	4.97
	Moody's first	32	1.135052	1.51	0.27	0.59	1.68	0.01	4.14
	Total	90	1.579948	1.61	0.17	1.24	1.92	0.01	4.97

Table 5b
Expected Duration in Distressed Regime Higher for EJ (Days)

Duration after Event		Sum of Squares	d.f.	Mean Square	*F*	Sig.
1 day	Between groups[a]	1.62	1	1.621774561	10.1846	0.002
	Within groups	14.01	88	0.159237568		
	Total	15.63	89			
2 days	Between groups	4.23	1	4.228522914	7.01452	0.010
	Within groups	53.05	88	0.60282399		
	Total	57.28	89			
3 days	Between groups	6.81	1	6.81461259	5.6007	0.020
	Within groups	107.07	88	1.216742149		
	Total	113.89	89			
4 days	Between groups	8.57	1	8.57049178	4.62304	0.034
	Within groups	163.14	88	1.853865231		
	Total	171.71	89			
5 days	Between groups	9.83	1	9.828392957	3.92024	0.051
	Within groups	220.62	88	2.507088296		
	Total	230.45	89			

[a] Groups are downgrades by EJ and Moody's.

the results of q_t between EJ and Moody's. From the figure we can infer that there is a higher persistence to a high-volatility regime for EJ than Moody's after the downgrade. Table 5a gives descriptive statistics on the persistency[14] of the distressed regime. We observe a consistent difference in the values of EJ and Moody's, something that is also observed through the F-statistics in Table 5b.

Another observation is that as the number of days increases away from the event day, the persistence of the distressed regime wears out. This can be observed by the increasing p-values (decreasing F-statistics) as the number of days away from the downgrade day increases. In the next section we explain how we capture the information value associated with the persistence of the high-volatility regime and also the timing of regime-switch around timely downgrades.

4.5 Cost Estimation for Daily Tendency of Distress: "Prob-Vol" Measure

Given that our model now has two regimes of equal mean ($\mu_1 = \mu_2$) but different volatility ($\sigma_1 \neq \sigma_2$), our proposed "Probability-Volatility"

[14] This is the equivalent of an n-day curtate future life expectancy in life contingencies.

(Prob-Vol) measure to capture daily stock return distress costs has to be adjusted. Therefore equation (3.7) becomes:

$$q_t \times (\mu_1^* - \mu_2^*) = q_t \times (\mathrm{d} \times (\sigma_2 - \sigma_1)). \quad (4.3)$$

In Figure 7 and 8 we demonstrate our Prob-Vol measure for an individual company and the entire sample respectively.

4.5.1 Example: An Individual Company, or the Equivalent of a "Dynamic Event Study"

In this section we provide an example of how the regime-switching model performs in the case of an individual company. We are looking at a company that has been downgraded by Egan Jones 257 days before Moody's below investment grade (from grade 10 to 11). Furthermore there is no additional noise for about a year before the event day (t = 101). For this company there is no other rating from EJ or Moody's for more than one year before. Figure 9 shows the stock price (bold line) and the probability of being in the undistressed regime (light line), 100 days before and after the event date. The stock returns process transitions between two regimes with a mean of −0.2948% and different volatility (σ_1 = 2.192%; σ_2 = 3.626%). The key to the regime-switching model is the daily probability of being in each regime since it is sensitive enough to follow periods of high volatility by switching to the distressed regime. This is obvious around day 35 and more obvious and persistent at about 15 days before the event date, which continues in the distressed regime for the next 60 days.

Our proposed (daily) measure to capture distress costs associated with downgrades is shown on Figure 7. The daily cost for this company can range from 0 (when q_t = 0) to 1.4338*d percentage points (when q_t = 1). We can then estimate an n-day cost by taking the summing q_t's over the n-day period and multiplying by the difference in

Figure 7
Daily "*Prob-Vol*" Measure (Individual Company)

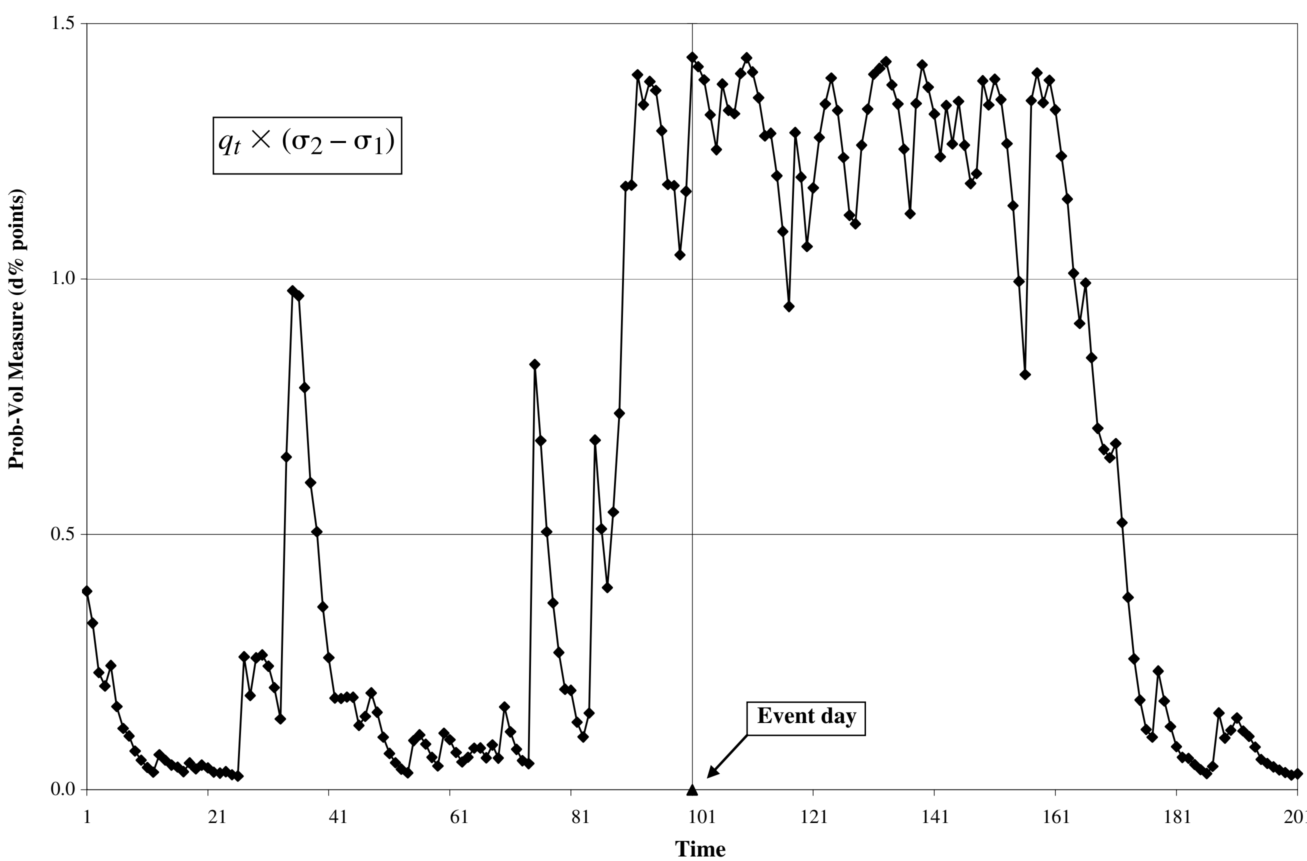


Figure 8
Average "*Prob-Vol*" Measure

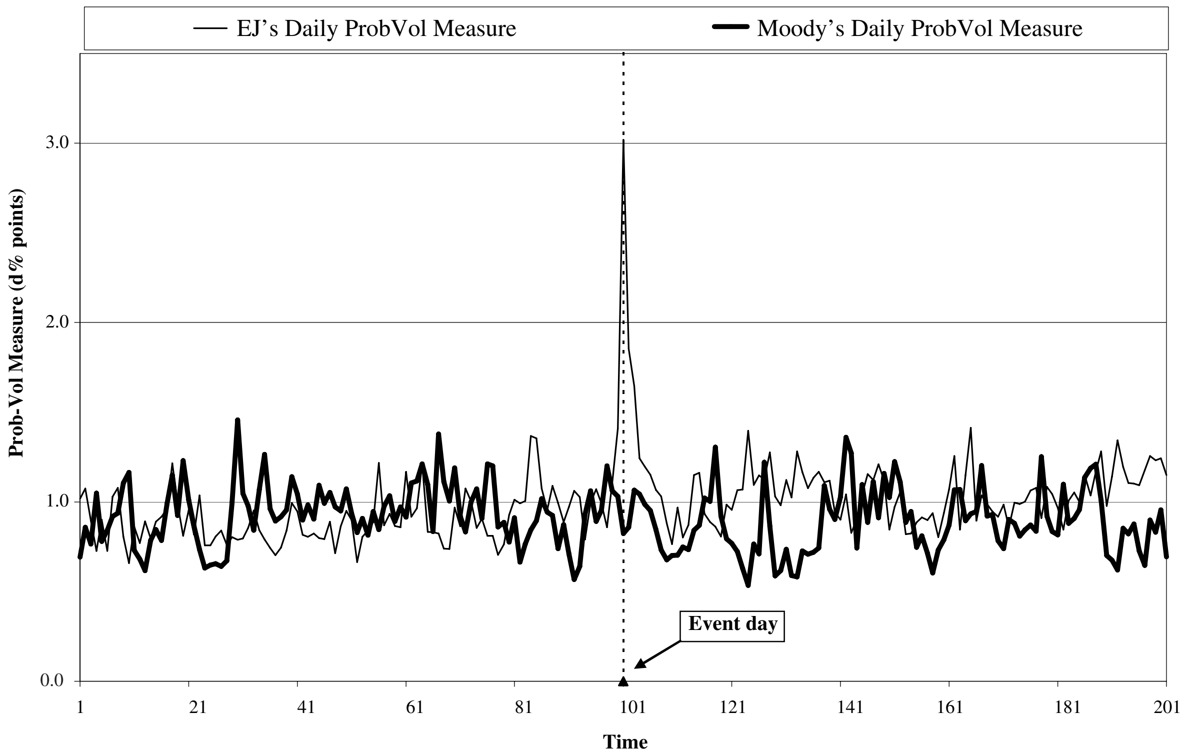
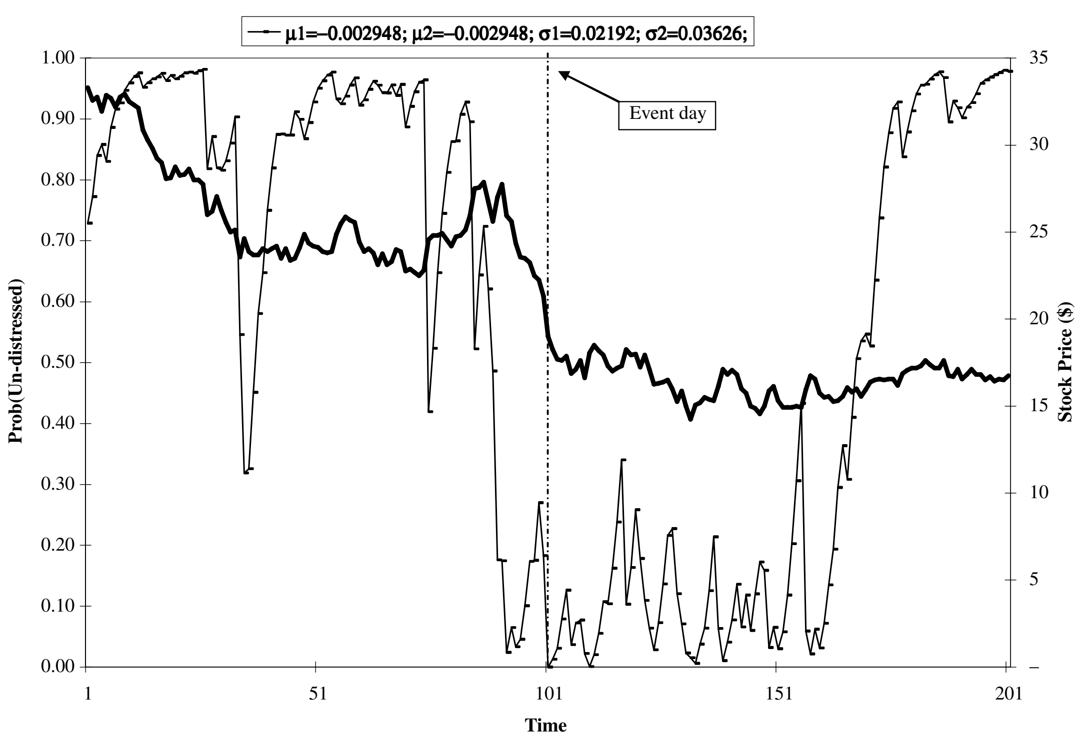


Figure 9
Stock Price vs. Prob(Undistressed Regime)



volatility. For example, the cost associated with a five-day window before and after the downgrade would sum to 14.07*d%.

4.5.2 In Aggregate

We complete this section by providing estimates of cumulative Prob-Vol costs for the period covering 20, 10, 5, 3, and 1 days, up to and including the event date (eq. 3.8). In Table 6 we show costs associated with timely downgrades from EJ and Moody's as well as for the entire sample. We estimate costs for the entire sample to be 21.07*d% for the period starting 20 days before the event day. Moreover costs for the 10-, 5-, and 3-day windows are 11.2*d%, 6.56*d%, and 4.6*d%, respec-

Table 6a

Descriptive Statistics for Cumulative "Prob-Vol" Cost (d* Percentage Points)

						95% Conf. Interval for Mean	
Period	Rating Comp.	*N*	Mean	Std. Dev.	Std. Error	Lower Bound	Upper Bound
$(t-20)$ to t	EJ first	58	23.02	15.35	2.02	18.98	27.05
	Moody's first	32	17.53	14.29	2.53	12.38	22.68
	Total	90	21.07	15.13	1.60	17.90	24.24
$(t-10)$ to t	EJ first	58	12.33	8.11	1.07	10.19	14.46
	Moody's first	32	9.16	8.03	1.42	6.26	12.05
	Total	90	11.20	8.18	0.86	9.49	12.91
$(t-5)$ to t	EJ first	58	7.38	5.48	0.72	5.94	8.82
	Moody's first	32	5.07	4.88	0.86	3.31	6.83
	Total	90	6.56	5.36	0.57	5.44	7.68
$(t-3)$ to t	EJ first	58	5.53	5.09	0.67	4.19	6.87
	Moody's first	32	2.92	3.02	0.53	1.83	4.00
	Total	90	4.60	4.62	0.49	3.63	5.57
$(t-1)$ to t	EJ first	58	4.43	4.61	0.61	3.21	5.64
	Moody's first	32	1.85	2.17	0.38	1.07	2.64
	Total	90	3.51	4.10	0.43	2.65	4.37
$(t-10)$ to $(t+10)$	EJ first	58	24.13	16.20	2.13	19.87	28.39
	Moody's first	32	17.72	14.95	2.64	12.33	23.11
	Total	90	21.85	15.99	1.69	18.50	25.20

Table 6b

Prob-Vol Cost Higher for EJ as Time to Event Decreases

Cumulative PV Measure		Sum of Squares	d.f.	Mean Square	*F*	Sig.
$(t-20)$ to t	Between groups[a]	620.59	1	620.591	2.763	0.100
	Within groups	19,762.25	88	224.571		
	Total	20,382.84	89			
$(t-10)$ to t	Between groups	207.04	1	207.043	3.169	0.079
	Within groups	5,749.44	88	65.334		
	Total	5,956.48	89			
$(t-5)$ to t	Between groups	110.60	1	110.600	3.976	0.049
	Within groups	2,448.07	88	27.819		
	Total	2,558.67	89			
$(t-3)$ to t	Between groups	141.34	1	141.339	7.065	0.009
	Within groups	1,760.46	88	20.005		
	Total	1,901.79	89			
$(t-1)$ to t	Between groups	136.54	1	136.543	8.857	0.004
	Within groups	1,356.62	88	15.416		
	Total	1,493.16	89			
$(t-10)$ to $(t+10)$	Between groups	846.66	1	846.659	3,402	0.068
	Within groups	21,897.77	88	248.838		
	Total	22,744.43	89			

[a] groups are downgrades by EJ and Moody's.

tively. We also estimate costs for the 10 days before and after the event date to be 21.85*d%.

Comparing cumulative costs between rating agencies, we find that EJ's downgrades are associated with significantly higher costs than Moody's as we move closer to the event date (Table 6b). Costs beginning at ($t - 20$) seem to be higher for EJ only at the 10% level, while costs beginning at ($t - 5$) can be differentiated at the 5% level. At this point, costs associated with EJ's downgrades are 7.38*d%, while the respective amount for Moody's is 5.07*d% ($p < 0.049$).

5. DISCUSSION

Our results are consistent with the Merton model as well as other finance studies on volatility estimates and the information value of bond ratings.

5.1 Change in Volatility and Equity-holders' Default Option

In a ''Merton world'' (Merton 1973, 1974, 1977) a newly issued debt can be thought of as a default (call) option of the borrowers (equity holders) on the value of assets with strike price equal to the face value or debt. Equity holders have the option to default on their debt payment without debt issuers being able to go after their personal assets (because of limited liability). In the case of default, the company's assets and equity will be liquidated and passed onto debt holders as a partial repayment of the company's obligation to them.

Equity holders may declare bankruptcy, in which case debt holders will be entitled to the company's assets up to the amount owed to them. Equity holders will have no claim on the company's assets until all debt is paid to debt holders. At the same time the personal assets of equity holders will be beyond the reach of the debt holders, thus the maximum amount bond holders will receive will be the minimum of the debt value and the value of equity remaining.

The value of the option to default on future debt obligations increases as the volatility of the underlying security increases (Black and Scholes 1973). Timely downgrades often coincide with a change to a higher-volatility regime around the time of the downgrade. Investors could potentially take advantage of the early warning (2- or 3-day window) that EJ provides through the set of timely downgrades we examine. Our results have two immediate implications: (1) the distance-to-default is expected to show a jump at the time of change in regime due to volatility increase and (2) the time series evolution of volatility as observed through a regime switching model can provide useful information for valuing derivatives on volatilities.

5.2 Information Value of Bond Ratings

Do changes in bond ratings add value? The literature does not give a clear answer to this question (Wakeman 1981; Goh and Ederington 1993; Hand, Holthausen, and Leftwich; 1992; Vassalou and Xing 2003). Given these results there is a tendency for ratings to lag and not lead a stock price reaction. In addition, Kliger and Sarig (2000) suggest that the reason some other papers (West 1973; Liu and Thakor 1984; Ederington, Yawitz, and Roberts 1987) suggest that bond ratings may help explain a cross-sectional variation in credit spreads may be because ratings could proxy for omitted variables in credit spreads.

What about bond-rating changes? A second strand of literature examines the relationship between ratings' changes and market prices. Kliger and Sarig (2000) suggest that ''The advantage of this approach is that each firm serves as its own control, which means that all pricing-relevant factors are controlled for.'' Authors who use this approach, however, still report conflicting results as to the information value of bond ratings (Grier and Katz 1976; Hettenhouse and Sartoris 1976; Weinstein 1977; Griffin and Sanvicente 1982; Ingram, Brooks, and Copeland 1983; Hand, Holthausen, and Leftwich 1992; Goh and Ederington 1993). Furthermore, Kliger and Sarig (2000) do not find a change in firm value when Moody's refines their rating scale with no fundamental change in rated companies' risk profile or public news announcement.

Our results on timely downgrades support that EJ bond ratings are timely and they give investors an early warning. This is because they react fast while the market is still absorbing the effect of new information through the tendency to trade in the high-volatility regime. However, we do not get the same result for Moody's.

Our results from Moody's timely downgrades suggest that there is an overall switching between the two regimes but we cannot identify a spike as in the case of EJ. A timely downgrade from Moody's could be implying the dissemination of private information or a possible miss by the non-NRSRO (EJ). In the case of releasing private information we would expect a tendency in stock returns to switch to the distressed regime (at the time or) after Moody's downgrade. In the case that Moody's is reacting to new public information, we would expect to see a pattern similar to EJ. However, our results do not differentiate between these two effects. This is also the case investigated by Pinches and Singleton (1978), who find that information from bond ratings are reflected in the stock price up to a year before the rating changes.

6. SUMMARY

Given the time lag established between NRSROs and non-NRSROs we measure the time-series (stock return) distress costs associated with a selected sample of downgrades from the two types of rating companies. We focus on both the timeliness and accuracy of a selected sample of bond downgrades from EJ (non-NRSRO) and Moody's (NRSRO), in order to (a) model changes in daily stock return regimes around the time of downgrades, (b) provide indications of distress costs emerging from regime switches, and (c) propose a set of risk measures based on the CAPM and the parameters of the regime-switching model to quantify these costs.

Our approach resembles a dynamic event study that produces consistent results with prior studies on the information value of bond ratings. We assume that stock returns switch from an undistressed (low-volatility) regime to a distressed (high-volatility) regime around the time of downgrades. We find that stock returns indeed show a tendency to switch from a low- to a high-volatility regime (1.92% vs. 6.10%) one day before the downgrade. Furthermore we estimate the long-term duration of the high-volatility regime given a downgrade to be about 3.2 days. Also, we estimate cumulative (stock return) distress costs to range from 18.5*d% to 25.2*d% for a window of 10 days before and after the time of downgrade.

Our results can be differentiated between EJ and Moody's. Interestingly, EJ seems to be downgrading on the day that the market exhibits the highest tendency to switch to the high-volatility regime. This represents an early warning to investors who could potentially exploit the expected duration of the high-volatility regime following the downgrade.

REFERENCES

BEAVER, W. H., C. SHAKESPEARE, AND M. T. SOLIMAN. 2006. Differential Properties in the Ratings of Certified vs. Non-Certified Bond Rating Agencies. *Journal of Accounting and Economics,* Fortheoming. https://faculty-gsb.stanford.edu/soliman/research.htm (retrieved July 20, 2006)

BLACK, F., AND M. SCHOLES. 1973. The Pricing of Options and Corporate Liabilities. *Journal of Political Economy* 81(3): 637–54.

BOLLEN, N. 1998. Valuing Options in Regime-Switching Models. *Journal of Derivatives* 6(1): 38–49.

EDERINGTON, L. H., J. B. YAWITZ, AND B. E. ROBERTS. 1987. The Informational Content of Bond Ratings. *Journal of Financial Research* 10: 211–26.

GOH, J. C., AND L. H. EDERINGTON. 1993. Is a Bond Rating Downgrade Bad News, Good News, or No News for Stockholders? *Journal of Finance* 48: 2001–08.

———. 1999. Cross-sectional Variation in the Stock Market Reaction to Bond Rating Changes. *Quarterly Review of Economics and Finance* 39: 101–12.

GOLDFELD, S. M., AND R. E. QUANDT. 1973. A Markov Model for Switching Regressions. *Journal of Econometrics* 1: 3–16.

GRIER, P., AND S. KATZ. 1976. The Differential Effects of Bond Rating Changes among Industrial Public Utility Bonds by Maturity. *Journal of Business* 49: 226–39.

GRIFFIN, P., AND A. Z. SANVICENTE. 1982. Common Stock Returns and Rating Changes: A Methodological Comparison. *Journal of Finance* 37: 103–19.

HAMILTON, J. D. 1989. A New Approach to the Economic Analysis of Non-stationary Time Series. *Econometrica* 57: 357–84.

HAMILTON, J. D., AND R. SUSMEL. 1994. Autoregressive Conditional Heteroskedasticity and Changes in Regime. *Journal of Econometrics* 64: 307–33.

HAND, J. R. M., R. W. HOLTHAUSEN, AND R. W. LEFTWICH. 1992. The Effect of Bond Rating Agency Announcements on Bond and Stock Prices. *Journal of Finance* 47: 733–52.

HARDY, M. R. 2001. A Regime Switching Model of Long Term Stock Returns. *North American Actuarial Journal* 5(2): 41–53.

HARRIS, G. R. 1997. Regime Switching Vector Autoregressions: A Bayesian Markov Chain Monte Carlo Approach. *Proceedings of the 7th International AFIR Colloquium* 1: 421–50.

HETTENHOUSE, G., AND W. SARTORIS. 1976. An Analysis of the Informational Value of Bond Rating Changes. *Quarterly Review of Economics and Business* 16: 65–78.

INGRAM, R., L. BROOKS, AND R. COPELAND. 1983. The Information Content of Bond Rating Changes: A Note. *Journal of Finance* 38: 997–1003.

JOHNSON, R. 2004. Rating Agency Actions around the Investment-Grade Boundary. *Journal of Fixed Income* 13(4): 25–37.

KLIGER, D., AND O. SARIG. 2000. The Information Value of Bond Ratings. *Journal of Finance* 55: 2902–79.

LIU, P., AND A. THAKOR. 1984. Interest Yields, Credit Ratings and Economic Characteristics of State Bonds: An Empirical Analysis. *Journal of Money, Credit and Banking* 16: 344–51.

MERTON, R. C. 1973. Theory of Rational Option Pricing. *Bell Journal of Economics and Management Science* 4: 141–83.

———. 1974. On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *Journal of Finance* 29: 449–70.

———. 1977. On the Pricing of Contingent Claims and the Modigliani-Miller Theorem. *Journal of Financial Economics* 5(2): 241–49.

PINCHES, G., AND J. SINGLETON. 1978. The Adjustment of Stock Prices to Bond Rating Changes. *Journal of Finance* 33: 29–44.

VASSALOU, M., AND Y. XING. 2003. Equity Returns Following Changes in Default Risk: New Insights into the Informational Content of Credit Ratings. Working Paper, Columbia University.

WAKEMAN, M. 1981. The Real Function of Bond Rating Agencies. *Chase Financial Quarterly*.

WATTS, R. 1977. Corporate Financial Statements, a Product of the Market and Political Processes. *Australian Journal of Management* 2: 53–75.

WEINSTEN, M. 1977. The Effect of Rating Change Announcement on Bond Price. *Journal of Financial Economics* 5: 29–44.

WEST, R. 1973. Bond Ratings, Bond Yields and Financial Regulation: Some Findings. *Journal of Law and Economics* 16: 159–68.

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