Rating History and the Rating Dynamics of Fallen Angels, Rising Stars, and Big Rating Jumpers

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Abstract

Using samples from Standard & Poor's CreditPro 2005 dataset, we estimate models of rating migration subsequent to firms that issue bonds becoming fallen angels (FAs), becoming rising stars (RSs), or experiencing historical rating jumps of at least two notches (big rating jumpers). Comparator issuers (peers) are identified for the foregoing groups and rating transition models are estimated for these peers. The results suggest that different models of rating transition may be needed for fallen angels, rising stars and big jumpers relative to their peers. In general, the impact of rating history on the probability of a rating transition varies according to the rating path that occurred prior to the current rating state.

JEL classification: C13, C14, C32, C34, C41, G14

Keywords: Survival analysis, proportional hazards, rating migration, rating history, non-Markovian behaviors, fallen angels, rising stars, big rating jumps.

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1. Introduction

Estimates of rating migration probabilities are important to the profitability of fixed income investments, to credit pricing decisions, and also to credit risk management and capital adequacy requirements under the BASEL II framework. Previous research suggests that rating migrations depend on rating history, for example the direction of a prior rating change impacts on the current migration probability, Hamilton and Cantor (2004). Given this dependence on rating history it is natural to ask whether one model fits all, or whether differing paths for rating history lead to different models. For example, do fallen angels exhibit the same dependence on rating history as other bonds? We estimate models of rating migration subsequent to firms that issue bonds becoming fallen angels, becoming rising stars, or experiencing historical rating jumps of at least two notches (big jumpers.) Comparator issuers (peers) are identified for the foregoing groups and rating transition models are estimated for these peers. For example, fallen angels with a speculative grade that are further downgraded are compared to other speculative grade issuers experiencing a downgrade.

The modelling of rating transitions has received substantial attention in the research literature. However, there has been little work that investigates non-Markovian rating dynamics for fallen angels, rising stars, and big jumpers. Comparing rating transition models for these issuers with the models for their peers, the results show that the significant variables differ. Furthermore, relative to their comparators, rating transitions for fallen angels, rising stars and big rating jumpers, generally show more dependence on rating history. The implication is that bond investors, banking institutions and regulators, may need to consider conditioning their models of transition probability on the path the issuer has followed to its current rating. If, for example, the issuer is a fallen angel then it may need a fallen angel model to get appropriate transition probabilities.

The paper is structured as follows: Section 2 provides a brief discussion of the literature. Section 3 presents the methods used, followed by a description of the data in Section 4. Section 5 summarizes the results of the estimation models. Section 6 summarizes the main findings of this research.

2. Literature Review

2.1. Non-Markovian behaviour

Previous empirical studies have found evidence of non-Markovian behaviours such as duration dependence, serial correlation, and path dependence in rating dynamics. For example, Atlman and Kao (1992) and Carty and Fons (1994) provided evidence of serial correlation in rating migrations. Lando and Skodeberg (2002) indicated that there is a negative relation between the migration probability and the length of time an issuer stayed in a particular rating. Hamilton and Cantor (2004) suggested that the direction of a prior rating change impacts on the migration probability. Figlewski, Frydman, and Liang (2006) also suggested that rating momentum exists, that is, a downgrade is more likely to be followed by a further downgrade than an upgrade. Altman (1998) found that newly rated firms, compared with seasoned firms of the same rating class, exhibit a smaller probability of rating migrations within a few years. Figlewski et al (2006) also provided evidence of an ageing effect. Specifically, the longer it is since a firm was first rated, the more likely it is that the firm would default.

2.2. Fallen Angels

Moody's study on fallen angels over the period 1982-2003 (Mann, Hamilton, Varma, and Cantor, 2003) found that fallen angels have higher probabilities of being upgraded to investment grade than their peers. Standard & Poors' study on fallen angels (Vazza, Aurora, Schneck, 2005) also found the same result. Mann *et al.* also reported that the ratings fallen angels received, at the time they were downgraded from investment to speculative grade, affected their default probability as well as their probability of returning to an investment grade.

3. Method

3.1. Hazards

The effect of rating history covariates on the duration of a rating grade is investigated using survival analysis. The resulting survivor function $S(t)$ =P $(T>t)$ gives the probability that the time of a rating transition T will exceed time t, conditional on variables that capture the firm's rating history. The survivor function can be conveniently derived from the hazard function. The hazard, roughly speaking, gives the expected rate of incidence of a rating transition over a short interval.[3] The hazard function is estimated using Cox's (1972) proportional hazards model.

3.2. Rating states and estimation

The focus of this study is the probability that a rating state for an issuer will change. The time in a rating state starts from the time the firm enters a rating class (starting rating) subsequent to the commencement date of the study (1 January, 1982). The state ends at the time the firm migrates to another rating class (ending rating). The time a firm keeps the same rating is the survival time and time is measured in years.

[3] The inverse of the hazard gives the expected duration conditional on survival until the start of period *t*.

If a firm exits from a rating class due to merger, extinction of firm's rated debt, the debt becoming unrated (NR), or any reason other than an up-grade or a down-grade, the survival time is treated as censored. In the upgrade model, down-state transitions (rating states with starting ratings better than ending ratings.) are censored and vice versa for downgrade models. Rating states commencing before the start of the model estimation period, or finishing after the end of the model estimation period, are also treated as censored.

The rating states are pooled for the period 1982-2005. Hazard models are then developed for the following sub-samples:

Fallen angels and their speculative grade rated peers

Rising stars and their investment grade rated peers

Firms with a previous big down jump in rating and their peers

Firms with a previous big up jump in rating and their peers

The use of repeated rating transitions for the same firm is likely to introduce dependence among the observations. This problem is reduced to the extent that covariates in the model control for dependence. To allow for any dependence, the Wei-Lin-Weissfeld method (Wei, Lin, Weissfeld, 1989) is used to get robust variance estimates. This method, however, does not correct for any bias in the coefficients. To account for ties, in which several firms experience the same rating migration event with the same survival period, it has been traditional to use approximation adjustments such as the Efron method. However, we use the exact method for handling ties provided in SAS Version 9.

3.3. The Model

The model to be estimated is:

$h(\mathbf{Z},t) = h(0,t) \exp^{\mathbf{Z}\beta}$

Where $h(\mathbf{Z},t)$ is the hazard for a rating transition at time t given the covariate vector **Z**.

$h(0,t)$ is the baseline hazard

β is the vector of estimated coefficients

The covariate vector **Z** contains the following variables, selected primarily on the basis of their significance in the prior ratings literature. However, some variables such as the length of lagged states and rate of prior changes in ratings are analogous to variables that Yao, Partington and Stevenson (2005) found significant in studying transitions in runs of stock prices.

Lag one: The duration (in years) of the non-censored state (with start rating different from ending rating) immediately preceding the current state (LAG_ONE).

Lag two: The duration (in years) of the non-censored state (with start rating different from ending rating) immediately preceding the lag one state (LAG_TWO).

Rate of prior rating change: This rate equals the number of rating changes observed between the entry of the firm to the study and the beginning of the current state divided by the period over which the changes were observed (RATE_PRIOR_CHANGE).

Original rating: the rating of the firm when it was first rated (ORIGINAL_RATING).

Start rating: The rating at the beginning of each rating state (START_RATING).

Age since first rated: The rating age of the firm, which is equal to the length in years from the time the firm was first rated until the beginning of the current state (AGE_SINCE_FIRST_RATED).

A prior not rated (NR) status: This variable takes the value of one if the firm experienced a NR status from the time it entered the study until the beginning of the current rating state, otherwise it is zero (DUMMY_NR).

A switch from an investment to a speculative (junk) grade: This variable takes the value of one if immediately prior non-censored rating state underwent a switch from an investment to a junk grade (fallen angel). This dummy variable indicates whether the rating state analyzed was a fallen angel (DUMMY_INV_JUNK_SWITCH).

A switch from a speculative (junk) to an investment grade: This variable takes the value of one if immediately prior non-censored rating state underwent a switch from a junk to an investment grade (rising star). This dummy variable indicates whether the rating state analyzed was a rising star (DUMMY_JUNK_INV_SWITCH).

We examine whether the start rating proximity to the investment / junk boundary states impacts on the upgrade / downgrade hazards of the issuers studied. Two dummy variables were used for this purpose. If the start rating of the current state is in the lower investment boundary, BBB-, BBB, BBB+, the dummy variable takes the value one, otherwise zero (DUMMY_SR_LOWER_INV), or if the start rating is in the junk boundary, BB-, BB, BB+ , the dummy takes the value one, otherwise zero (DUMMY_SR_JUNK_BOUNDARY).

Dummy variables were also created as control variables representing the industry sector of each firm. Thirteen sectors were categorized by Standard & Poor's in the CreditPro2005 dataset. Firms in the financial institution sector were excluded from the sample leaving twelve industry sectors. The firm's industry dummy is coded one if it was in the sector and zero otherwise. The insurance sector was left un-coded in order to avoid perfect collinearity in the industry dummies. The industry sectors are listed in Table 1.

Unlike most studies on rating dynamics, which just focuses on the coarser rating categories (AAA, AA), we employ finer rating sub-categories such as AAA, AAA-. The rating scales, which take into account plus and minus signs, are coded from 0 to 26 with 0 indicating the default state (D) and 26 indicating the AAA state. Details of the rating codes are provided in Table 1. The higher the value of a rating variable (original rating, start rating), the better the quality of the firm at the corresponding time. A similar coding technique was employed by Kim and Wu (2006) to examine the impacts of sovereign credit ratings history on international capital inflows to emerging countries, and on the development of the financial sectors in these countries. The numeric conversion maintains the rank order of the rating but assumes that the difference between any two consecutive rating states is the same. The alternative of coding each rating class through dummy variables would consume a substantial number of degrees of freedom and would also hinder clear and compact presentation of the results.

TABLE 1 HERE

4. Data

Rating data was obtained from Standard & Poor's CreditPro2005. The rating behavior of US's fallen angels, rising stars, and big jumpers is examined over the time horizon 1982 – 2005. This period covered different phases of the credit and business cycles in the US.

The high yield bond market in the US was established as a substantial market in the first half of the 1980s. The year 1986 saw a record of 52 fallen angels representing 4.21% of investment grade issuers that year, Standard and Poors (2005). Rating migrations consequent to the establishment of the high yield bond market from the middle of the 1980s constitute an important source of events for the study.

The period 1990 to 2005 covers one full business cycle for the US and many developed markets. The period started with a recessionary year followed by a long expansion in the US economy. There was a growth in rising stars which peaked in 1997. Since then the number of rising stars has been declining and has been outnumbered by fallen angels. The incidence of fallen angels steadily increased during the economic slowdown in early 2000s, and peaked at 2002 with 146 fallen angels, representing 4.65% of the 3139 investment grade issuers that year, Standard and Poors (2005).

4.1. Fallen Angels

The dataset includes 541 fallen angel (FA) firms. These are cases which were downgraded from investment grade to speculative (junk) grade in the non-censored transition immediately prior to the current state. From the current state for these 541 fallen angels, 278 experience further downgrades (FA down states), 62 undergo an up-grade but remain junk rated (FA up-to-junk states), and 89 experience an up-grade to investment rated (FA up-to-investment states).

Peer group samples were established as follows. A random sample of 541 speculative (junk) rated issuer states was selected as a peer group for the fallen angels. These peers were sampled from issuers that had not experienced a FA event but had a junk rating. From the current state for these 541 speculative grade rated peers, 264 undergo down-grades (peers of FAs down-states), 91 experience up-grades to junk classes (Peers of FAs up-to-junk states), 34 undergo up-grades to investment classes (peers of FA up-to-investment states). Statistics for state lengths of fallen angels and their peers are given in Table 4.

TABLE 4 HERE

4.2. Rising stars

The dataset includes 429 rising star (RS) states, which were recently upgraded from junk to investment grade immediately prior to the current state. From the current state for these 429 rising stars, 153 experience upgrades (RS up states), 76 undergo a down-grade back to junk rated (RS down-to-junk states), and 35 experience a down-grade but remain investment rated (RS down-to-investment states).

Peer group samples were established as follows. A random sample of 429 investment grade rated issuer states was selected., These peers were sampled from issuers that had not experienced a RS event but were rated investment classes. From the current state for these 429 investment grades rated peers, 88 undergo up-grades (peers of RS up-states), 12 experience down-grades to junk classes (Peers of RS down-to-junk states), 201 undergo down-grades to investment classes (peers of RS down-to-investment states). Statistics for state lengths of rising stars and their peers are given in Table 5.

TABLE 5 HERE

Histograms of state lengths of fallen angels and rising stars are depicted in Figure1. Both FA and RS distributions tend to have a positive skew.. For fallen angels, the histograms suggest that further declines in credit rating tend to be swift, while improvements tend to take much longer. In contrast, for rising stars improvements in ratings tend to happen more quickly than worsening ratings.

FIGURE 1 HERE

4.3. Big down jumpers

We define a big down jumper as a firm who recently experienced a big down jump in credit rating of at least two notches in their non-censored rating transitions immediately prior to the current rating. The dataset includes 2088 big down jumpers, of which 1317 subsequently experience down-grades and 400 subsequently experience up-grades.

The peer group for the big down jumper sample includes 2088 issuer states. These peer issuer states have experienced a lag one down state but not a lag one big down jump. Of the 2088 peers, 1124 end in down-grade states (peers of big down jump down states) and 329 end in up-grade states (peers of big down jump up-states). Statistics for state lengths of big down jumpers and their peers are given in Table 3.

TABLE 3 HERE

4.4. Big up jumper

A big up jumper is a firm who recently experienced a big jump up in credit rating of at least two notches. The dataset includes 769 big up jumpers, of which 233 subsequently experience down-grades and 248 subsequently experience up-grades.

The peer group for the big up jumper sample includes 769 issuer states. These peer states have experienced a lag one up state but not a lag one big jump up. Of the 769 peers , 232 are down-grade states (peers of big up jump down states) and 274 are up-grade states (peers of big up jump up-states). Statistics for state lengths of big up jumpers and their peers are given in Table 2.

TABLE 2 HERE

Histograms of state lengths of big down jumpers and big up jumper are depicted in Figure 2. Both big down jumpers and big up jumpers have non normal distribution. For big down jumpers, the histograms show a clear tendency for further downgrades to follow quickly, but for up grades to take substantially longer. On the other hand, for big up jumpers, transitions to down states tend to arise more slowly than transitions to up states.

FIGURE 2 HERE

5. Results

5.1. FAs, RSs and their peers.

The following model is estimated for RSs and their respective peers

$$h(t)=h_0(t) \exp \{ \beta_1 \text{ Lag\_one} + \beta_2 \text{ Lag\_two} + \beta_3 \text{ Rate\_prior\_change} + \beta_4 \text{ Original\_rating} + \beta_5 \text{ Start\_rating} + \beta_6 \text{ Age\_since\_first\_rated} + \beta_7 \text{ Dummy\_NR} + \beta_8 \text{ Dummy\_SR\_lower\_inv} + \sum_{k=1}^{11} \beta_k D_{sector\_k} \}$$

A similar model, except that the covariate *dummy_SR_lower_inv* is replaced by the covariate *dummy_SR_junk_boundary* , is developed for FAs and their peers.

The results of the models for FAs and their peers are presented in Table 6 while the results of the models for RSs and their peers are shown in Table 7.

TABLE 6 HERE

TABLE 7 HERE

In interpreting Table 6 and 7, a negative coefficient reduces the hazard and therefore reduces the probability of a rating migration. For example, in the model for peers of FA down states (Table 6), an increase in the length of the lag one rating state by one year reduces the chance of a down-grade by (1-0.973) or 2.7%.

The impacts of rating history on the migration hazards of FAs and RSs are markedly different from the impacts on the hazards of their respective peers. For instance, the migration hazards of FA down states and FA up to junk states depend significantly on several rating history covariates, whereas the hazard of their peers depend only on their start rating (start_rating) and a prior NR status (dummy_NR). Similarly, the migration hazards of RS down-to-junk states depend significantly on several rating history covariates while the hazard of their peers just depends on the rate of prior rating changes (rate_prior_change).

FAs/ RSs states and their respective peers, in some cases, are impacted in opposite ways by certain rating history covariates. For instance, a higher rate of prior rating change (rate_prior_change) increases the hazards of FA up-to-investment states but decreases the hazards of their peers. An older rating age (age_since_first_rated) increases the migration hazards of RS up-states but decreases the hazards of their peers.

Regarding the impacts of significant rating history covariates on the migration hazard of FAs and RSs states, a shorter lag one rating state (lag_one), a lower start rating (start_rating) and being in junk boundary states BB-, BB, BB+ (Dummy_SR_junk_boundary=1) increase the hazards of FAs migrating within their junk states. A better original rating will increase the up-grade hazards of FAs and decrease the down-grade hazards of RSs. The older the RS is (age_since_first_rated), the higher the hazards of RS migrating within their investment states.

5.2. Big up/ big down jumper and their respective peers

The following model is developed for big up jumpers and their respective peers

$$r(t)=r_0(t)\exp\{\beta_1 \text{ Lag\_one} + \beta_2 \text{ Lag\_two} + \beta_3 \text{ Rate\_prior\_change} + \beta_4 \text{ Original\_rating} + \beta_5 \text{ Start\_rating} + \beta_6 \text{ Age\_since\_first\_rated} + \beta_7 \text{ Dummy\_NR} + \beta_8 \text{ Dummy\_SR\_junk\_boundary} + + \beta_9 \text{ Dummy\_junk\_inv\_switch} + \beta_{10} \text{ Dummy\_SR\_junk\_boundary} + \beta_{11} \text{ Dummy\_SR\_lower\_inv} + \sum_{k=1}^{11} \beta_k D_{sector\_k}\}$$

A similar model, except that the covariate *dummy_junk_inv_switch* is replaced by the covariate *dummy_inv_junk_switch*, is developed for big down jumpers and their respective peers

The results of the models for rating states with historical big up jumps / big down jumps and their peers are presented in Table 8.

TABLE 8 HERE

First of all, big jumpers down states are more affected by their rating history than are their respective peers. For instance, original rating (original_rating) has a significant negative impact on the hazards of big jumpers down states but no effect on their peers. On the other hand, up states with a historical big up jump are less influenced by the rating history compared with their peers. For example, the length of the lag one/ lag two rating state (lag_one, lag_two), and rating age (age_since_first_rated) do not have significant impacts on the hazards of up-states with a historical big up jump but do impact on their peers.

The statistically significant impacts other rating history covariates impose on the migration hazards of big rating jumpers varies according to their rating path. For instance, only states with a historical big down jumps and their peers are (negatively) influenced by the length of the lag one rating state (lag_one), and only down-states with a historical big down jump and their peers are (positively) influenced by the rate of prior rating change (rate_prior_change). For those with a historical big up jump, being in the boundary of speculative (junk) or investment grades reduce the migration hazards of down-states (and their peers) but increase the hazards of up states (increase up-grade momentum). For down states with a historical big down jump, having experienced a switch from investment to junk grades (Fallen angels) or currently being in the investment grade boundary reduce their migration hazards (reduce down-grade momentum)..

6. Conclusion

Using samples from Standard & Poor's CreditPro 2005 dataset, the Cox proportional hazard model was used to investigate the rating dynamics of fallen angels

(FA), rising stars (RS) and firms with historical big rating jumps (big rating jumpers) over the period 1982-2005.

The results show that the impacts rating history imposed on the migration hazards of FAs, RSs, and big rating jumpers are different from those of their peers. FAs down states, FAs up-to-junk states, and for RS all states are more influenced by the rating history than are their respective peers while FAs up-to-investment states are less affected by rating history compared with their peers. Big rating jumpers and their peers also tended to have different statistically significant predictors. In some cases, FAs, RSs and their respective peers, were impacted in opposite ways by some rating history covariates.

The results of this study are relevant for fixed income portfolio managers, banking institutions and regulators. As fallen angels and big down jumpers, especially FA down-states, FA up-to-junk states, and down-states with a historical big down jump, show more dependence on the rating history, internal rating based models and credit stress tests should take into account the rating path the issuer has followed to its current rating state. Most importantly, separate hazard models should be developed to account for the varying risk of rating changes of issuers with different historic rating paths.

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Table 1 **Variable dictionary**

	Description			Codes/ Values				
First_rated_date	Date the firm was first rated							
Start_date / End_date	The starting date / ending date of each rating state							
Duration	The length of a rating state		Years	(End date -	(Start date-1)) / 365			
Age_since_first_rated	Rating age (since it was first rated) at state entry		Years	(Start_date -(First_rated_date-1)) / 365				
Start_rating	The starting rating at the beginning of each rating state	0=D	3=C+	7=CCC-	11=B	15=BB+	19=A-	23=AA
Original_rating	The orginial rating when the firm was first rated	1=C-	4=CC-	8=CCC	12=B+	16=BBB-	20=A	24=AA+
		2=C	5=CC	9=CCC+	13=BB-	17=BBB	21=A+	25=AAA-
			6=CC+	10=B-	14=BB	18=BBB+	22=AA-	26=AAA
Lag_one	The length of the non-censored lag one rating state		Years	(Lag one's end date - (Lag one's start date -1))/365				
Lag_two	The length of the non-censored lag two rating state		Years	(Lag two's end date - (Lag two's start date -1))/365				
Rate_prior_change	A measure of rating volatility		(The number of prior rating changes) / The number of years a firm spent in the study					
Dummy_NR	Dummy variable indicating whether the firm underwent a Not Rated (NR) status during the time it spent in the study							
Dummy_lag_down	Dummy variable indicating whether the non-censored immediate prior rating state was a down state							
Dummy_lag_up	Dummy variable indicating whether the non-censored immediate prior rating state was an up state							
Dummy_junk_inv_switch	Dummy variable indicating whether the non-censored immediate prior rating state underwent a switch from speculative (junk) to investment grade							
Dummy_inv_junk_switch	Dummy variable indicating whether the non-censored immediate prior rating state underwent a switch from investment to speculative (junk) grade							
Dummy_big_jump_down	Dummy variable indicating whether the non-censored immediate prior rating state underwent a down jump of at least 2 notches, for instance from A to BBB+							
Dummy_big_jump_up	Dummy variable indicating whether the non-censored immediate prior rating state underwent an up jump of at least 2 notches, for instance from B- to B+							
Dummy_SR_junk_boundary	Dummy variable indicating whether the start rating of the analyzed rating state is in the speculative (junk) grade boundary (BB-, BB, BB+)							
Dummy_SR_lower_inv	Dummy variable indicating whether the start rating of the analyzed rating state is in the investment grade boundary/lower investment grades (BBB-, BBB, BBB+)							
Sector *	Firm's sector coded as a dummy variable							
	Aerospace / automotive / capital goods / metal	Insurance		Forest and building products / homebuilders				
	Consumer / service sector	Leisure time / media		Health care / chemicals				
	Energy and natural resources	Real Estate		Transportation				
	Telecommunications	Utility		High technology/ computers/ office equipment				

[*] 13 Sector categories were provided by Standard & Poor's in CreditPro 2005 dataset. Financial institutions were excluded from the sample

Table 2: Duration Statistics of big-up-jump states vs. their respective peers, 1982-2005

Model	Number of non-censored states	Non-censored states/ sample size*	Mean (years)	Median (years)	Standard Deviation	Skewness	Kurtosis	Min (days)	Max (years)
Big -up-jump Down-states	233	30.30%	2.90	2.23	2.45	1.57	2.57	5 days	12.66
Lag-one-up Down-states (peers)	232	30.17%	3.69	2.87	3.04	1.69	3.32	15 days	17.71
Big-up-jump Up-states	248	32.25%	2.10	1.38	2.15	2.87	11.01	7 days	14.83
Lag-one-up Up-states (peers)	274	35.60%	2.22	1.67	1.77	1.75	3.35	9 days	10.24

* sample size includes 769 states

Table 3: Duration Statistics of big-down-jump states vs. their respective peers, 1982-2005

Model	Number of non-censored states	Non-censored states/ sample size*	Mean (years)	Median (years)	Standard Deviation	Skewness	Kurtosis	Min (days)	Max (years)
Big-down-jump Down-states	1317	63.07%	0.92	0.35	1.51	4.19	26.10	2 days	15.83
Lag-one-down Down-states (peers)	1124	53.83%	1.50	0.81	1.98	3.19	13.97	3 days	17.46
Big-down-jump Up-states	400	19.15%	1.94	1.39	1.74	1.84	5.78	2 days	13.14
Lag-one-down Up-states (peers)	329	15.75%	2.64	2.00	2.15	2.24	7.09	2 days	14.33

* sample size includes 2088 states

Table 4: Duration statistics of fallen angels (FA) states vs. their respective peers, 1982-2005

Model	Number of non-censored states	Non-censored states/ sample size*	Mean (years)	Median (years)	Standard Deviation	Skewness	Kurtosis	Min (days)	Max (years)
FA down states	278	51.38%	1.11	0.63	1.48	4.44	35.38	2 days	15.83
Speculative (junk) grade rated down states (peers)	264	48.79%	0.77	0.40	0.93	1.89	3.70	3 days	5.16
FA up- to- junk states	62	11.46%	1.95	1.45	1.44	0.94	0.34	36 days	6.05
Junk grade rated up-states (peers)	91	16.82%	1.61	1.23	1.25	0.99	0.26	7 days	5.38
FA up-to-investment states	89	16.45%	2.42	2.51	1.57	1.65	6.76	2 days	10.44
Investment grade rated up-states (peers)	34	6.28%	1.65	1.57	0.91	0.79	0.67	39 days	4.12

* sample size includes 541 states

Table 5: Duration statistics of rising stars (RS) states vs. their respective peers, 1982-2005

Model	Number of non-censored states	Non-censored states/ sample size*	Mean (years)	Median (years)	Standard Deviation	Skewness	Kurtosis	Min (days)	Max (years)
RS up states	153	35.66%	2.38	1.55	2.17	1.68	2.63	16 days	11.34
Investment grade rated up states (peers)	88	20.50%	2.87	2.11	2.41	2.21	6.69	41 days	14.83
RS down-to-junk states	76	17.70%	3.09	2.45	2.54	1.77	3.56	8 days	11.86
Junk grade rated down states (peers)	12	2.79%	1.20	1.33	0.67			44 days	2.40
RS down-to-investment states	35	8.15%	2.34	1.91	1.93	2.39	8.16	117 days	10.41
Investment grade rated down states (peers)	201	46.85%	2.73	2	2.63	2.02	5.04	9 days	14.84

* sample size includes 429 states

Table 6 : **Models for fallen angels (FAs) versus their speculative (junk) grade rated peers**

Variables	FAs down-states versus their peers						FAs up-to- investment states versus their peers						FAs up-to-speculative (junk) states versus their peers					
	FAs down states			Speculative (junk) grade rated down states (peers)			FAs up-to-investment states			Investment grade rated up states (peers)			FAs up-to-junk states			Junk grade rated up states (peers)		
	Parameter estimate	Standard error	Hazard ratio	Parameter estimate	Standard error	Hazard ratio	Parameter estimate	Standard error	Hazard ratio	Parameter estimate	Standard error	Hazard ratio	Parameter estimate	Standard error	Hazard ratio	Parameter estimate	Standard error	Hazard ratio
Lag_one	**-0.16844***	0.05152	0.845	-0.02717	0.0449	0.973	-0.02953	0.07378	0.971	**-0.33744*****	0.1761	0.714	**-0.20779****	0.09993	0.812	-0.06438	0.06537	0.938
Lag_two	0.03957	0.02704	1.04	0.06187	0.04122	1.064	0.01089	0.05487	1.011	**-0.44402****	0.19964	0.641	**-0.1483*****	0.08861	0.862	-0.0879	0.07922	0.916
Rate_prior_change	0.08578	0.10528	1.09	0.12491	0.24838	1.133	**0.36357***	0.06124	1.438	**-3.93065***	1.41517	0.02	**-2.05194***	0.70211	0.128	0.0088	0.34985	1.009
Original_rating	**-0.078***	0.02059	0.925	-0.0002175	0.02587	1	**0.07676*****	0.03936	1.08	**0.11699*****	0.06351	1.124	**0.10207*****	0.05498	1.107	0.0296	0.04327	1.03
Start_rating	**-0.25733***	0.08279	0.773	**-0.26941***	0.03401	0.764	**1.0464***	0.20396	2.847	**1.26729***	0.37189	3.551	**-0.61948***	0.12739	0.538	**-0.32964***	0.08096	0.719
Age_since_first_rated	**0.03876***	0.01308	1.04	0.01618	0.01881	1.016	-0.03012	0.02344	0.97	**-0.09075*****	0.05063	0.913	**-0.11349***	0.03103	0.893	0.01428	0.03201	1.014
Dummy_NR	**-1.06571***	0.2137	0.344	**-1.3304***	0.24732	0.264	**-0.68236*****	0.35369	0.505	0.05941	0.62882	1.061	**-0.95931****	0.47793	0.383	**-1.25443***	0.46581	0.285
Dummy_SR_junk_ boundary	**1.0763***	0.35002	2.934	0.04062	0.19754	1.041	-1.25839	0.95423	0.284	**13.87955***	1.10699	1066132	**1.95892***	0.72658	7.092	0.56601	0.40341	1.761
Sec_Aerospace_ automotive	-0.96569	0.27923	0.381	0.13071	0.25815	1.14	-0.19496	0.62032	0.823	-2.22105	0.86616	0.108	-0.11352	1.10507	0.893	0.2127	0.71722	1.237
Sec_Consumer_service	-0.57106	0.27591	0.565	0.28341	0.24074	1.328	-0.92772	0.65762	0.395	-1.26932	0.61953	0.281	0.60516	1.08477	1.832	-0.35321	0.72742	0.702
Sec_Energy_ natural_resources	-0.6586	0.42658	0.518	-0.15666	0.33288	0.855	-0.53601	0.70848	0.585	-1.1691	0.63902	0.311	-0.46149	1.20934	0.63	-0.25802	0.77172	0.773
Sec_Forest_ building_products	-0.50345	0.32898	0.604	-0.11997	0.38007	0.887	-1.48511	0.68247	0.226	-1.39162	0.60362	0.249	0.78378	1.13787	2.19	-0.2638	0.72313	0.768
Sec_Healthcare_ chemicals	-0.67114	0.31449	0.511	0.03338	0.33789	1.034	-1.09381	0.71043	0.335	-0.76827	0.63462	0.464	0.11787	1.15558	1.125	-0.18569	0.81182	0.831
Sec_High_technology_ computers	-0.26147	0.33459	0.77	-0.49815	0.37954	0.608	-0.86239	0.8513	0.422	-17.80483	0.77393	0	1.01795	1.2581	2.768	-0.29923	0.78728	0.741
Sec_Telecommunications	0.37406	0.41768	1.454	0.43896	0.3015	1.551	0.62822	1.01129	1.874	-17.23886	1.36222	0	-13.22221	1.18396	0	0.28548	0.8362	1.33
Sec_Leisure_time_ media	-1.6771	0.50187	0.187	-0.15305	0.27687	0.858	0.2093	0.64178	1.233	-1.52342	1.04446	0.218	-0.08855	1.20308	0.915	0.3356	0.76336	1.399
Sec_Real_estate	-0.77362	0.54121	0.461	-1.13394	0.70727	0.322	-1.04569	0.75317	0.351	-18.05241	0.94796	0	-13.58641	1.21498	0	0.40485	1.28728	1.499
Sec_Transportation	-0.61876	0.3305	0.539	0.00669	0.51222	1.007	-0.03771	0.62504	0.963	-18.73479	0.94671	0	0.18707	1.19544	1.206	0.22452	0.93202	1.252
Sec_Utility	-0.52601	0.28845	0.591	-0.56399	0.40503	0.569	-0.502	0.632	0.605	-1.08932	0.59325	0.336	1.12211	1.07611	3.071	0.68462	0.77193	1.983

* p ≤ 1%, ** 1%< p ≤ 5%, *** 5%< p ≤10% based on Wald chi-square tests

Table 7: Models for rising stars (RSs) versus their investment grade rated peers

Variables	RS up-states versus their peers						RS down-to-investment states versus their peers						RS down-to-speculative (junk) states versus their peers					
	RSs up states			Investment grade rated up states (peers)			RS down-to-investment states			Investment grade rated down states (peers)			RSs down-to-junk states			Junk grade rated down states (peers)		
	Parameter estimate	Standard error	Hazard ratio	Parameter estimate	Standard error	Hazard ratio	Parameter estimate	Standard error	Hazard ratio	Parameter estimate	Standard error	Hazard ratio	Parameter estimate	Standard error	Hazard ratio	Parameter estimate	Standard error	Hazard ratio
Lag_one	-0.28086*	0.10092	0.755	-0.01693	0.04881	0.983	-0.06	0.17351	0.942	-0.01644	0.02833	0.984	-0.36047**	0.17419	0.697	-0.51825	0.337	0.596
Lag_two	-0.00929	0.05744	0.991	-0.1237***	0.07012	0.884	-0.20505	0.13296	0.815	-0.03227	0.03045	0.968	-0.15049	0.10165	0.86	-0.29856	0.18227	0.742
Rate_prior_change	0.40766***	0.22842	1.503	0.03977	0.34215	1.041	-0.28246	1.261	0.754	0.2331	0.25564	1.263	-1.56584**	0.68812	0.209	-1.25379***	0.74569	0.285
Original_rating	0.00489	0.02487	1.005	0.03741	0.04442	1.038	-0.14613**	0.0582	0.864	0.00511	0.02525	1.005	-0.05803***	0.03071	0.944	0.10405	0.11616	1.11
Start_rating	-0.09738	0.1468	0.907	-0.25085**	0.10085	0.778	0.54482*	0.18361	1.724	0.05164	0.07561	1.053	-1.76227*	0.67848	0.172	-0.42666	0.51165	0.653
Age_since_first_rated	0.04464***	0.02504	1.046	-0.04466***	0.02624	0.956	0.12149**	0.04999	1.129	0.05299*	0.01776	1.054	0.05669	0.03612	1.058	-0.18248	0.14255	0.833
Dummy_NR	-1.19508*	0.23464	0.303	-1.4643*	0.4885	0.231	-1.71505**	0.72935	0.18	-1.6357*	0.34633	0.195	-1.13892*	0.33023	0.32	-0.50792	0.98214	0.602
Dummy_SR_lower_inv	1.51969**	0.72782	4.571	-0.30293	0.37918	0.739	0.17956	0.93882	1.197	-0.0142	0.26468	0.986	-4.3568*	1.48042	0.013	0.65878	1.31256	1.932
Sec_Aerospace_ automotive	-0.32565	0.35397	0.722	-0.31385	0.39061	0.731	0.28911	1.00036	1.335	0.16562	0.29549	1.18	0.15986	0.34363	1.173	1.30243	1.17368	3.678
Sec_Consumer_service	-0.96799	0.42444	0.38	-1.37028	0.52252	0.254	0.6635	1.08794	1.942	0.11133	0.30872	1.118	-1.90257	0.56819	0.149	1.85332	1.24848	6.381
Sec_Energy_ natural_resources	-0.38627	0.4813	0.68	0.3263	0.7562	1.386	0.89024	1.16529	2.436	0.89553	0.43494	2.449	-0.1489	0.54121	0.862	-14.68218	1.36175	0
Sec_Forest_ building_products	-1.21521	0.48265	0.297	-14.77738	0.47569	0	-0.15626	1.31753	0.855	1.05718	0.35531	2.878	-0.76334	0.57039	0.466	1.55013	1.3719	4.712
Sec_Healthcare_ chemicals	-0.5116	0.40177	0.6	-0.17188	0.47897	0.842	1.49902	0.96784	4.477	0.14489	0.45975	1.156	-0.82157	0.49581	0.44	1.66147	1.47499	5.267
Sec_High_technology_ computers	0.20335	0.43021	1.225	-0.32724	0.51764	0.721	-12.98652	0.90868	0	0.43086	0.34919	1.539	0.52074	0.57735	1.683	1.31021	1.26973	3.707
Sec_Telecommunications	-0.53983	0.71309	0.583	-0.20175	0.52723	0.817	2.48422	0.98836	11.992	-0.65371	0.41272	0.52	-12.756	1.04088	0	-13.00824	1.50929	0
Sec_Leisure_time_ media	-0.04694	0.39579	0.954	-0.59936	0.70128	0.549	-0.15625	1.19803	0.855	1.40249	0.32797	4.065	-0.77373	0.55508	0.461	-14.50457	1.39373	0
Sec_Real_estate	-1.25312	0.99642	0.286	-0.2359	0.82081	0.79	-13.17313	1.08338	0	-0.56389	0.93759	0.569	0.14873	0.94641	1.16	-15.55161	1.46696	0
Sec_Transportation	-0.86221	0.46742	0.422	-1.08087	0.84659	0.339	-0.10753	1.56895	0.898	-0.17497	0.37908	0.839	-0.0975	0.52578	0.907	1.09733	1.44394	2.996
Sec_Utility	-0.4836	0.35053	0.617	-0.63943	0.32629	0.528	0.73617	0.93093	2.088	0.00453	0.26761	1.005	-0.86944	0.5002	0.419	-0.15785	1.46049	0.854

* $p \leq 1\%$, ** $1\% < p \leq 5\%$, *** $5\% < p \leq 10\%$ based on Wald chi-square tests

Table 8: Models for big rating jumpers versus their peers

Variables	Up states with a lag one big down jump vs. their peers^						Down states with a lag one big down jump vs. their peers^^					
	Big-down-jump Up-states			Lag-one-down up-states (peers)			Big-down- jump Down-states			Lag-one-down down-states (peers)		
	Parameter estimate	Standard error	Hazard ratio	Parameter estimate	Standard error	Hazard ratio	Parameter estimate	Standard error	Hazard ratio	Parameter estimate	Standard error	Hazard ratio
Lag_one	**-0.10793***	0.033	0.898	**-0.08043****	0.03227	0.923	**-0.04512***	0.01608	0.956	**-0.02447*****	0.0145	0.976
Lag_two	-0.0008352	0.02394	0.999	**-0.11108***	0.0328	0.895	0.02102	0.01393	1.021	-0.00411	0.01225	0.996
Rate_prior_change	-0.03672	0.0842	0.964	-0.13816	0.18409	0.871	**0.07686*****	0.04449	1.08	**0.20495****	0.09706	1.227
Original_rating	**0.07172***	0.01775	1.074	**0.0739***	0.02619	1.077	**-0.04064***	0.0103	0.96	-0.018	0.01352	0.982
Start_rating	**-0.19108***	0.02216	0.826	**-0.21943***	0.02825	0.803	**-0.09351***	0.01134	0.911	**-0.0592***	0.01499	0.943
Age_since_first_rated	**-0.01809*****	0.01019	0.982	-0.0187	0.01359	0.981	**0.01862***	0.00589	1.019	**0.0131****	0.00649	1.013
Dummy_NR	**-1.16724***	0.20619	0.311	**-1.00592***	0.20231	0.366	**-1.31963***	0.1301	0.267	**-1.05178***	0.11934	0.349
Dummy_SR_junk_ boundary	**0.61706***	0.15946	1.853	-0.04016	0.17058	0.961	-0.0415	0.10899	0.959	**-0.2298****	0.1006	0.795
Dummy_SR_lower_inv	0.13571	0.17427	1.145	0.10449	0.14286	1.11	**-0.2309****	0.09363	0.794	-0.10248	0.07864	0.903
Dummy_junk_inv_ switch	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Dummy_inv_junk_switch	-0.16111	0.17131	0.851	**0.38583*****	0.22664	1.471	**-0.29034****	0.11769	0.748	0.05189	0.15909	1.053
Sec_Aerospace_ automotive	0.09115	0.21401	1.095	-0.36612	0.2369	0.693	-0.30014	0.1366	0.741	0.20767	0.13831	1.231
Sec_Consumer_ service	-0.02708	0.21695	0.973	-0.6047	0.23842	0.546	-0.08203	0.13385	0.921	0.15312	0.13096	1.165
Sec_Energy_ natural_resources	-0.18036	0.26735	0.835	-0.40663	0.30419	0.666	-0.27951	0.17947	0.756	-0.23622	0.17855	0.79
Sec_Forest_ building_products	-0.31318	0.33489	0.731	-0.56651	0.27419	0.568	-0.3253	0.18975	0.722	-0.0779	0.16752	0.925
Sec_Healthcare_ chemicals	-0.05329	0.26137	0.948	-0.53184	0.2975	0.588	-0.22267	0.17473	0.8	-0.01783	0.1636	0.982
Sec_High_technology_ computers	0.49757	0.28246	1.645	-0.43431	0.32968	0.648	-0.29478	0.17736	0.745	0.00188	0.19444	1.002
Sec_Telecommunications	0.33299	0.27202	1.395	-0.39723	0.35706	0.672	-0.00692	0.16086	0.993	0.12019	0.17935	1.128
Sec_Leisure_time_ media	-0.07349	0.24949	0.929	-0.4526	0.31467	0.636	-0.27992	0.15572	0.756	0.11208	0.16263	1.119
Sec_Real_estate	-0.902	0.63278	0.406	-0.94625	0.49208	0.388	-0.25332	0.23934	0.776	-0.19218	0.37579	0.825
Sec_Transportation	-0.26847	0.23742	0.765	-0.71794	0.28743	0.488	-0.50005	0.16002	0.606	-0.12894	0.19023	0.879
Sec_Utility	0.24554	0.2059	1.278	-0.12869	0.20774	0.879	-0.19551	0.13969	0.822	-0.28921	0.1348	0.749

Variables	Up states with a lag one big up jump vs. their peers^^^						Down states with a lag one big up jump vs. their peers^^^^					
	Big-up-jump up-states			Lag-one-up Up states (peers)			Big-up- jump Down-states			Lag-one-up Down-states (peers)		
	Parameter estimate	Standard error	Hazard ratio	Parameter estimate	Standard error	Hazard ratio	Parameter estimate	Standard error	Hazard ratio	Parameter estimate	Standard error	Hazard ratio
Lag_one	-0.02339	0.05294	0.977	**-0.14186***	0.04157	0.868	0.03962	0.04347	1.04	-0.03823	0.03857	0.962
Lag_two	0.06236	0.03984	1.064	**-0.08862****	0.0405	0.915	**-0.08509*****	0.04614	0.918	-0.00595	0.03524	0.994
Rate_prior_change	0.1244	0.15139	1.132	0.27016	0.20211	1.31	0.19901	0.17244	1.22	0.41977	0.35554	1.522
Original_rating	**0.03615****	0.01752	1.037	0.02498	0.02113	1.025	**-0.06529***	0.01988	0.937	-0.02904	0.02467	0.971
Start_rating	**-0.1703***	0.02367	0.843	**-0.18929***	0.02789	0.828	**-0.03936*****	0.02449	0.961	**-0.05559*****	0.03407	0.946
Age_since_first_rated	-0.00564	0.0191	0.994	**0.02873*****	0.01594	1.029	**0.04246****	0.01652	1.043	**0.05311****	0.01833	1.055
Dummy_NR	**-1.65149***	0.27054	0.192	**-0.9755***	0.23743	0.377	**-1.61443***	0.24376	0.199	**-1.21731***	0.24014	0.296
Dummy_SR_junk_ boundary	**0.51548***	0.16115	1.674	**0.49302***	0.15245	1.637	**-0.55651***	0.20108	0.573	**-0.49582****	0.24799	0.609
Dummy_SR_lower_inv	**0.87106***	0.2526	2.389	0.12476	0.18082	1.133	**-0.5959****	0.25774	0.551	**-0.35056*****	0.20773	0.704
Dummy_junk_inv_ switch	-0.19443	0.2654	0.823	-0.07229	0.24425	0.93	0.41288	0.25853	1.511	-0.30885	0.31326	0.734
Dummy_inv_junk_switch	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Sec_Aerospace_ automotive	-0.09114	0.26236	0.913	-0.87063	0.24119	0.419	-0.50082	0.2546	0.606	0.2984	0.28271	1.348
Sec_Consumer_ service	-0.42595	0.30469	0.653	-0.94821	0.26341	0.387	-0.19782	0.25715	0.821	0.30369	0.28667	1.355
Sec_Energy_ natural_resources	-0.33258	0.29284	0.717	-1.11884	0.29099	0.327	-0.96754	0.42382	0.38	-0.06017	0.44906	0.942
Sec_Forest_ building_products	-0.47421	0.41012	0.622	-1.28099	0.28713	0.278	-0.47836	0.35708	0.62	0.05221	0.39028	1.054
Sec_Healthcare_ chemicals	-0.32065	0.30954	0.726	-0.50834	0.2431	0.601	-0.49991	0.28191	0.607	0.05062	0.34756	1.052
Sec_High_technology_ computers	-0.22835	0.42582	0.796	-0.93793	0.35581	0.391	-0.10913	0.36992	0.897	-0.26249	0.48029	0.769
Sec_Telecommunications	-0.145	0.47675	0.865	-0.7662	0.27892	0.465	0.32266	0.28823	1.381	0.16231	0.33791	1.176
Sec_Leisure_time_ media	0.193	0.31721	1.213	-0.98075	0.25582	0.375	-0.08739	0.29731	0.916	0.34519	0.35532	1.412
Sec_Real_estate	-12.19581	0.61374	0	-0.98044	0.75861	0.375	-1.08523	1.17299	0.338	-12.35981	0.64561	0
Sec_Transportation	0.0382	0.28538	1.039	-0.50925	0.39992	0.601	-0.87799	0.43696	0.416	-0.11037	0.56885	0.896
Sec_Utility	0.03156	0.25294	1.032	-0.69732	0.19119	0.498	-0.50594	0.25364	0.603	-0.0712	0.26341	0.931

* $p \leq 1\%$, ** $1\% < p \leq 5\%$, *** $5\% < p \leq 10\%$ based on Wald chi-square tests

^ Big-down-jump up states are up states with the non-censored immediate prior rating state underwent a down jump of at least 2 notches (dummy_big_jump_down=1). Their peers are up states with the non-censored immediate prior rating state experienced a downgrade of 1 notch (dummy_lag_down =1 and dummy_big_jump_down=0)

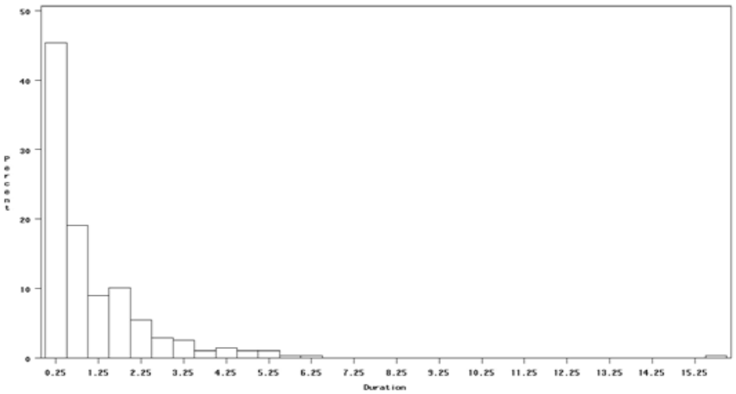
^^ Big-down-jump down states are down states with the non-censored immediate prior rating state underwent a down jump of at least 2 notches (dummy_big_jump_down=1). Their peers are down states with the non-censored immediate prior rating state experienced a downgrade of 1 notch (dummy_lag_down =1 and dummy_big_jump_down=0)

^^^ Big-up-jump up states are up states with the non-censored immediate prior rating state underwent an up jump of at least 2 notches (dummy_big_jump_up=1). Their peers are up states with the non-censored immediate prior rating state experienced an upgrade of 1 notch (dummy_lag_up=1 and dummy_big_jump_up=0)

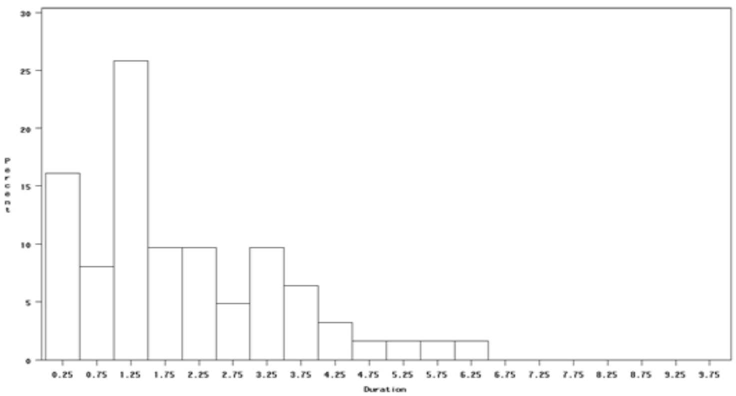
^^^^ Big-up-jump down states are down states with the non-censored immediate prior rating state underwent an up jump of at least 2 notches (dummy_big_jump_up=1). Their peers are down states with the non-censored immediate prior rating state experienced an upgrade of 1 notch (dummy_lag_up=1 and dummy_big_jump_up=0)

Figure 1

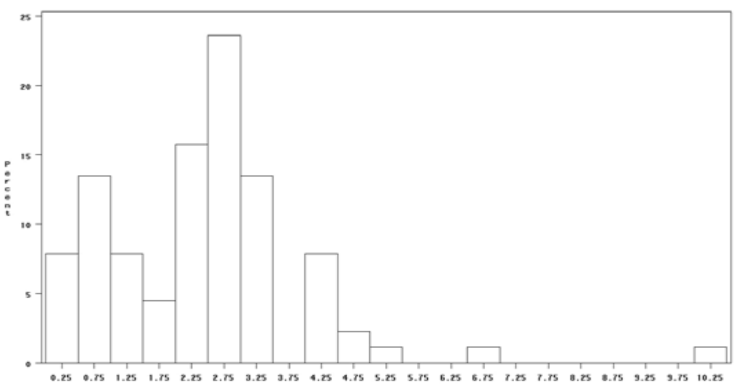
Histogram of the length of fallen angel down-states, 1982-2005



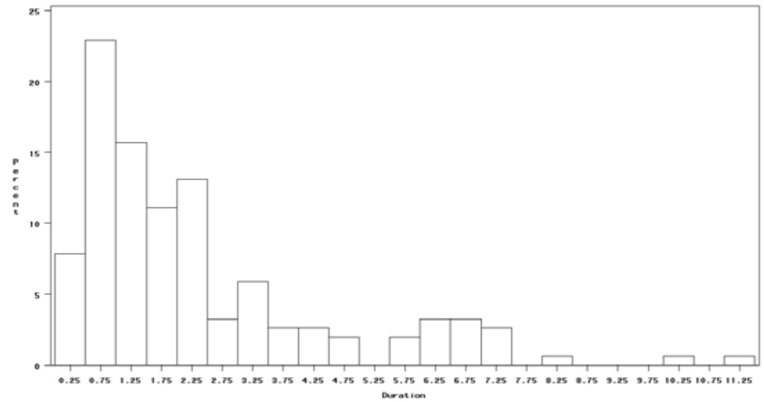
Histogram of the length of fallen angel up-to-junk states, 1982-2005



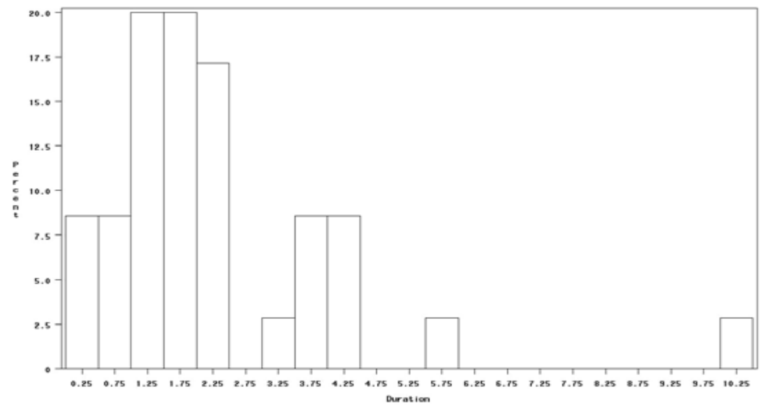
Histogram of the length of fallen angel up-to-investment states, 1982-2005



Histogram of the length of rising star up-states, 1982-2005



Histogram of the length of rising star down-to-investment states, 1982-2005



Histogram of the length of rising star down-to-junk states, 1982-2005

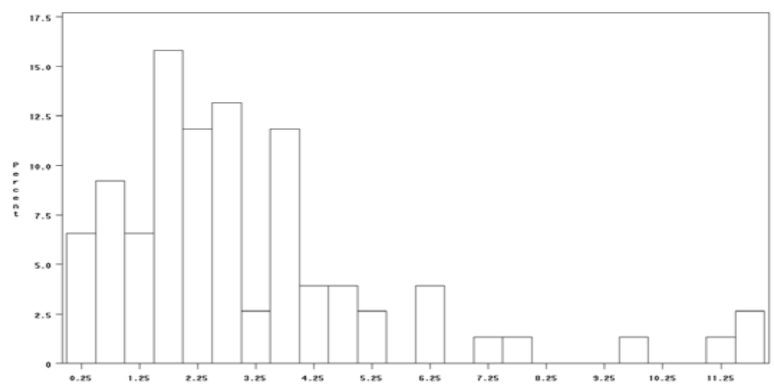
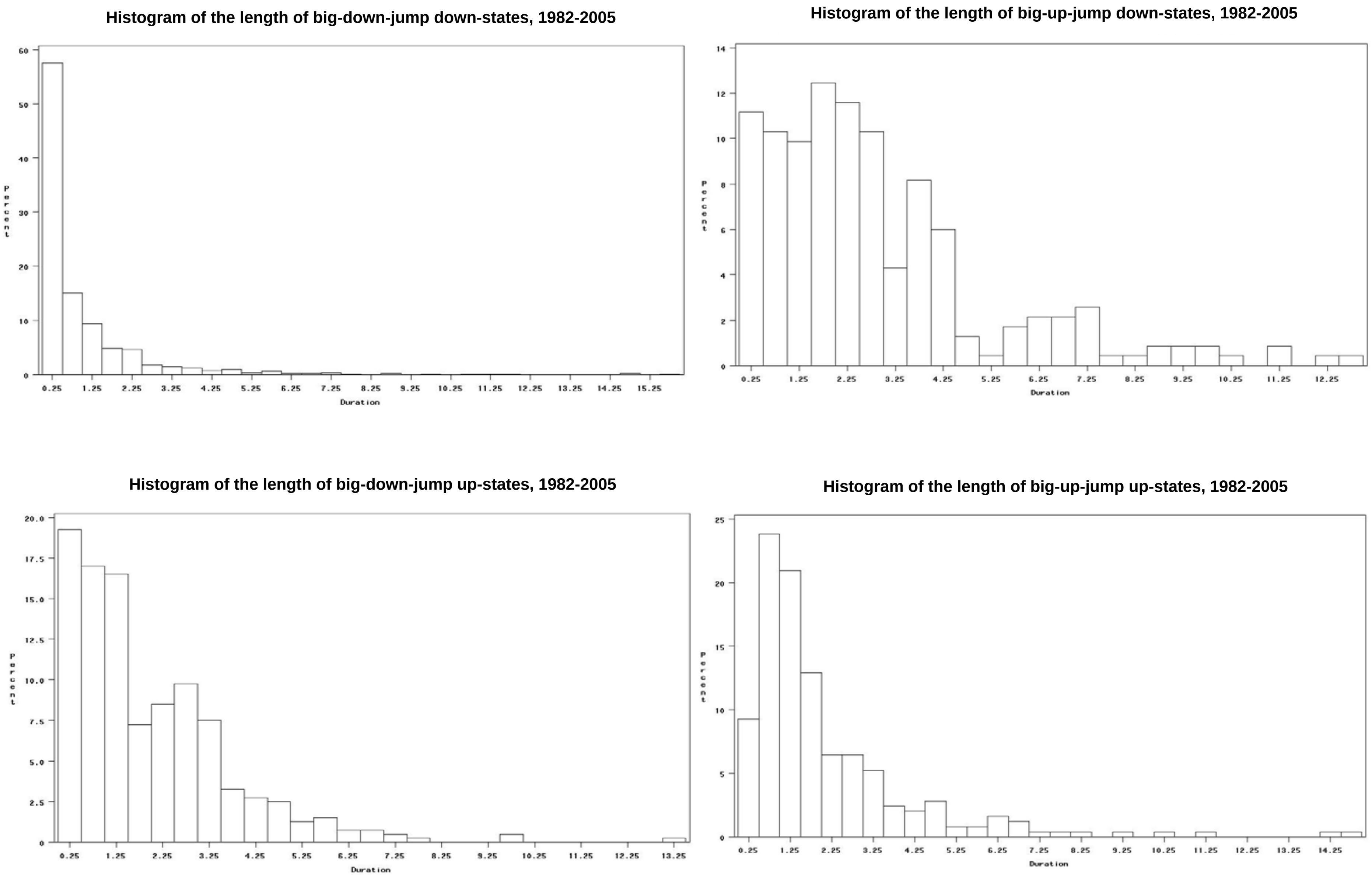


Figure 2


Histogram of the length of big-down-jump down-states, 1982-2005
Percent
Duration
Histogram of the length of big-up-jump down-states, 1982-2005
Percent
Duration
Histogram of the length of big-down-jump up-states, 1982-2005
Percent
Duration
Histogram of the length of big-up-jump up-states, 1982-2005
Percent
Duration