Issuer-heterogeneity and time-heterogeneity in the rating migration dynamics of financial institutions[1]

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Abstract

This study develops hazard models to examine the rating migration dynamics of financial institutions (FI) in the U.S during January 1984-March 2010. The proposed dynamic Cox's hazard model with time-varying covariates overcomes some limitation of the discrete time cohort Markov framework commonly used by credit rating agencies to estimate a rating migration matrix. It is found that in the absence of the current rating several aspects of rating history, macro-economic environment and political business cycle substantially affect migration hazards. These aspects jointly exhibit good (modest) ability in discriminating survived FIs from downgraded (upgraded) FIs. A large proportion of FIs that subsequently downgraded were flagged as downgrade "candidates" in advance of their actual migrations. The evidences of issuer-dependence and time-dependence in the migration dynamics are reinforced after controlling for the current rating. The information contained in the current rating is "incremental" compared to the information provided by rating history and macro-economic factors. Adding the current rating does not improve the discrimination power of the downgrade and upgrade models. The findings explicitly rule out the Markov and time-homogeneity properties inherent in the static Markov framework.

Keywords: Credit rating, issuer-heterogeneity, time-heterogeneity, hazard model, time varying covariate, forecast accuracy

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1. Introduction

Since the Basel II framework came into effect, credit ratings have been much used by banks to assess counterparty credit risks and to determine capital adequacy requirements. Banks are highly leveraged and interconnected. A concern for any bank is to adopt an appropriate approach in modeling rating migration probabilities of its counterparties, particularly financial institutions (FIs), as a small change in a migration probability estimate may result in a substantial variation in regulatory capital requirement. Jafry and Schuermann (2004) suggested that the estimation method chosen matters both statistically and economically. Changing estimation approaches leads to more variation in economic risk capital than switching between contraction and expansion.

The discrete time cohort Markov framework has been widely used by credit rating agencies (CRAs) to construct a rating migration matrix. The probability an issuer migrates from the current rating grade (*start rating*) to a new rating grade (*end rating*) is derived from the relative frequency of past rating changes. The estimation process does not account for rating withdrawals and the survival times of issuers in the dataset. The framework assumes that the rating process is independent of rating history and is static. The current rating alone determines the probability of a subsequent re-grade. The Markov and time-homogeneity assumptions have been challenged by numerous studies on rating behaviours.

The literature suggests the Markov property does not persist at a horizon longer than one or two years (Kiefer and Larson, 2007; Frydman and Schuermann, 2008). Issuers of the same grade migrate at different rates and heterogeneity exists after controlling for business cycles and industry sectors (Frydman and Schuermann, 2008). The source of issuer-heterogeneity can be attributed to a variety aspect of rating history[2]. There is also strong evidence that the time-homogeneity property does not persist long-term. Rating stability varies over time and ratings move pro-cyclically[3]. The evidences emphasize the need to control for issuer-dependence and time-dependence in modeling rating migrations.

The collapse of investment grade-rated FIs during the financial crisis has raised concerns on the opaque methodologies CRAs employ to assess issuers' creditworthiness. There is ongoing interest in developing a robust rating system that accurately captures the credit quality of FIs and that has a predictive power for future rating changes. Regulators need to identify impaired FIs at an early stage, thereby reducing the likelihood of financial distress and mitigating remedial costs. Accurately estimating the migration probabilities of FIs may aid regulators in developing an early warning system as an effective off-side monitoring tool. Such modeling requires an understanding of the rating behaviors of FIs.

Most previous studies on corporate rating dynamics focused on non-financial institutions. This study explores the rating behaviors of FIs, with a focus on issuer-heterogeneity and time-heterogeneity and aims to answer the following questions: (i) How well does the current rating explain and forecast future rating changes?; (ii) Whether and how issuer-heterogeneity and time-heterogeneity affect subsequent re-grades in (a) the absence of the current rating and (b) the presence of the current rating?; (iii) What is the predictive accuracy of issuer- and time-heterogeneity in forming time-varying migration probabilities?; and (iv) Does forecast performance change after controlling for the current rating?

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[2] See, for example, Altman and Kao (1992a, 1992b), Carty and Fons (1993), Nickell, Perraudin and Varotto (2000), Kavvathas (2001), Bangia, Diebold, Kronimus, Schagen, and Schuermann (2002), Lando and Skodeberg (2002), Hamilton and Cantor (2004), Kadam and Lenk (2008), Figlewski, Frydman and Liang (2008)

[3] See Altman and Kao (1991), Blume, Lim, MacKinlay (1998), Nickell et al. (2000), Kavvathas (2001), Bangia et al. (2002), Block and Vaaler (2004), Koopman, Lucas, and Monteiro (2006)

This study develops a robust empirical model that overcomes some limitations of the conventional discrete time cohort Markov approach. Cox's hazard model (Cox, 1972) was chosen to estimate the probability that a FI survives (from a downgrade/ an upgrade) in its current rating grade (*start rating)* at any point in time *t* over the time horizon *T*. The power and the flexibility of Cox's hazard model make it ideally suited to model rating migrations. It captures the duration at risk of each FI[4] and does not make assumptions about the distribution of survival times (Allison, 1995, p. 183). It can account for repeated migrations of the same issuer and accommodate different migration routes. It can be adapted to model non-proportional hazards and permits a rigorous testing of issuer-heterogeneity and time-heterogeneity. The model also offers the possibility to generate time-varying survival estimates that are dynamic in nature and have predictive power[5].

The study, employing a rich issuer rating dataset of FI's in the U.S. over an extended period, contributes to the literature as follows. First, new evidence is offered on issuer-dependence and time-dependence in rating migration dynamics of FIs. This is the first study offering a thorough understanding of the rating behaviors of FIs during the period January 1984-March 2010. Second, the study contributes to the framework for estimating rating migration probability by developing dynamic Cox's hazard models, which capture the evolution of macro-economic environment and political business cycle. The use of time-varying covariates in modeling rating migrations is appealing as the credit risk of a FI tends to be more affected by the recent macro environment than that prevailing at the beginning of the study. Third, there is current interest in estimating time-varying survival probabilities of FIs for credit risk management purpose. The study overcomes the computational challenges involved in forming

[4] Jafry and Schuermann (2004) suggested that there are efficiency gains when using duration approaches to estimate economic risk capital requirement

[5] It is suggested that Cox's proportional hazard model "identified failed and healthy banks with a high degree of accuracy", and "flagged a large proportion of banks that subsequently failed as potential failures in periods prior to their actual demise" (Whalen, 1991, p. 21)

time-varying probability survival estimates when the proportional assumption of the conventional Cox's hazard model (Cox, 1972) does not hold. The dynamic forecasts may aid regulators in the early detection of impaired FIs. Fourth, the study presents new evidence on the predictive ability of current rating, rating history, macro-economic environment and the political business cycle in estimating survival probabilities out-of-sample.

It is found that in the absence of the current rating a variety of past rating behaviors, macro-economic conditions, and the political business cycle impact strongly on the prospective rating distribution of FIs. For example, a downgrade at lag one raises the risk of a subsequent downgrade by over 200 percent. An increase in inflation rate or industrial production growth by one percent raises the downgrade hazard by over 400 percent and the upgrade probability by around 200 percent respectively. The effect of rating history is more pronounced after incorporating the current rating. Compared with some aspects of rating history and the macro-economic environment, the current rating has a relatively modest effect.

The current rating alone exhibits poor forecast performance out-of-sample. Rating history, macro-economic factors, and political business cycle jointly exhibit good (modest) ability in discriminating survival observations from downgraded (upgraded) observations. Controlling for the current rating does not improve the discriminatory power of the downgrade and upgrade models. The findings explicitly rule out the Markov and time-homogeneity properties inherent in the discrete time cohort Markov framework commonly used by CRAs.

The remainder of this paper is structured as follows. Section 2 reviews the literature, Section 3 describes the methods and variables employed, Section 4 presents the data, Section 5 presents the results, and Section 6 summarises the key findings, limitations, and implications of the study.

2. Literature review

2.1. Markov property

The effect of the current rating on rating stability and future rating distribution has been widely documented in the literature[6]. Issuers in the investment and speculative grade boundary exhibit different propensities compared with their peers in different rating grades. They are more likely to ascend the rating spectrum than to become fallen angels (Carty and Fons,1993; Carty, 1997). Given FIs' capital and confidence sensitive business nature, it is useful to examine how being in the boundary between investment and speculative rating grades affect the probability of a subsequent rating change.

2.2. Issuer-heterogeneity

Issuer-heterogeneity in corporate rating dynamics can be attributed to a variety of rating history aspects such as the original rating, rating age, serial correlation, duration dependence, and a fallen angel event.

The impact of rating history can be traced back to the original rating. Issuers with different original ratings show different migration dynamics and retain their original ratings in different ways[7]. The time since an issuer was first rated also affects the future rating distribution (Altman, 1998, pp. 1239-1240). Issuers of new bonds generally receive the face value of the issue and have sufficient cash flow to service their debts. They therefore have lower credit risk and may retain their original ratings for a longer period of time than their peers with seasoned bonds. It is unlikely that a default would occur to a bond during the first year of issue, and the first rating will only be revised if a substantial decline in credit quality is

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[6] See, for example, Lucas and Lonski (1992), Carty and Fons (1993), Carty (1997), Hamilton and Cantor (2004), Jorion, Shi, and Zhang (2005), Figlewski et al. (2008)

[7] See Altman and Kao (1991, 1992a, 1992b), Jorion et al. (2005), Figlewski et al. (2008)

imminent. In light of the above, the original rating and the period since a FI was first rated are included in the model.

It is widely documented that rating downgrades exhibits serial correlation[8]. This evidence reflects CRAs' practice to mitigate rating volatility, to be ex-post credible (Posch, 2006) and to "dole out the bad news in small doses rather than savaging the bond issuer all in one go" (Economist, 1997 in Loeffler, 2005, p. 374). The evidences of rating stability and serial correlation are consistent with the policy of rating bounce avoidance (Loeffler, 2005). The literature highlights the need to control for serial correlation in estimating rating migration probabilities.

The varying effects of lagged rating durations on future rating changes have been documented by Carty and Fons (1993) and Lando and Skodeberg (2002). The negative duration effect and serial correlation discussed above capture CRAs' practice to revise rating grades gradually by one notch at a time through a "series of mild downgrades" (Lando and Skodegerg, 2002, pp. 437-440), and to "limit rating reversal and dampen rating volatility" (Hamilton and Cantor, 2004, p. 3). Lando and Skodeberg (2002) also suggest that duration dependence and downward momentum are not as strong for FIs as for issuers in other sectors. Based on the literature, the durations of lagged rating states are incorporated in the model. The evidence also supports the use of the Cox's hazard model, which controls for the duration dependence without making any assumption about the functional form of that dependence.

An increase in rating volatility, with downgrades surpassing upgrades, has been observed over time[9]. Issuers staying a short period in sub-investment grades tend to experience high re-grades and default (Koopman et al., 2006). Issuers who, on their journey downward, make a

[8] See Altman and Kao (1992a, 1992b), Carty and Fons (1993), Kavvathas (2001), Bangia et al. (2002), Lando and Skodeberg (2002), Hamilton and Cantor (2004), Figlewski et al. (2008)

[9] See Altman and Kao (1991), Lucas and Lonski (1992), Lando and Skodeberg (2002)

short transit through the middle grades are likely to fall to lower grades (Lando and Skodeberg, 2002). In addition, a one notch rating change in low rating grades implies a larger increase in default risk (Jorion and Zhang, 2007). This evidence emphasises the need to account for rating volatility and prior rating levels in estimating rating migration hazards. The prior rating level was also used by Bannier and Hirsch (2010) to capture any effect arisen from changing sample composition as time unfolds.

Rating migration across investment/ speculative grade boundary (BBB-/BB+) has received considerable attention in the literature (Mann, Hamilton, Varma, and Cantor, 2003; Vazza, Aurora, and Schneck, 2005). Fallen angels are riskier than their peers following their fall date. They exhibit strong downward momentum, experience a rapid migration rate until reaching their lowest rating grades, and are vulnerable to default. However, over extended periods, fallen angels possess robust franchise value, enhanced business strength and improved profitability. They exhibit a greater tendency to survive and to rebound strongly after surviving the initial years of financial distress. Compared with their peers, fallen angels have better debt structures (Mann et al., 2003, p. 2) and are more likely to return to investment grades in the long term. This raises the question of whether different rating paths lead to different rating distributions. As FIs are capital and confidence-sensitive entities, it is difficult for them to compete and operate sustainably once they lose their investment grade ratings. The study examines how being a fallen angel/ a rising star affects a FI's migration hazard.

The study also explores some additional aspects of rating history which has received little attention in the literature, such as a substantial rating change and a prior rating withdrawal. Rating changes of multiple notches are less frequently observed than single-notch changes, which reflects CRAs' practice to "keep large magnitude rating changes" to a minimum (Carty and Fons, 1993, p. 10). A substantial rating change and a rating withdrawal may occur for several reasons. Does a substantial rating change reflect a substantial decline or improvement in the credit risk of a FI or merely reflect an "unusual sensitivity to credit quality of a particular occurrence" given FI's capital and confidence-sensitive business nature (Standard & Poor's, 2001)? Does a rating withdrawal signal an imminent decline in the credit quality of a FI or merely occur because the issuer no longer carries significant debt? The study extends the literature by examining how a substantial rating change and a rating withdrawal affect FI's probability of a rating migration.

In addition to rating history, industry risk constitutes another source of issuer-heterogeneity in rating dynamics. Volatility of future revenues varies across industry sectors (Kadam and Lenk, 2008) and each industry faces an upper-limit rating (Galil, 2003). Combining macro-economic and industry factors yields the best fitting model (Berd, 2005). The study therefore incorporates sub-sectors of FIs to capture the sub-sector risk of each issuer.

2.3. Time-heterogeneity

There is strong evidence that rating dynamics differ in times of recession and growth (Bangia et al., 2002). Downgrades and defaults occur more often during periods of contraction whereas upgrades occur more often during periods of growth. Rating volatility decreases during business cycle peaks and increases during troughs (Nickell et al., 2000). Rating migrations are principally affected by macro-economic factors rather than the characteristics of debt issues (Blume, Keim, and Patel, 1991). Low ratings are more vulnerable to adverse macro conditions than high ratings. The sensitivity of ratings to business cycles can be attributed to the fact that CRAs show excessive optimism/ pessimism in revising ratings during economic growth/ recession (Amato and Furfine, 2003). According to Bangia et al. (2002, p. 469), failure to incorporate macro-economic factors in credit risk models may lead to an underestimation of "downward potential of high yield portfolio" in contractions or "suboptimal capital allocation in lending business."

In addition to the state of the economy, the political business cycle may be another source of time-heterogeneity in rating behaviours. Block and Vaaler (2004) observed an increase in sovereign rating downgrades during the years when national elections occur. The literature is rather silent on the effect of the political business cycle on corporate ratings. It is suggested that the calling and aftermath of national elections correlate with fiscal, monetary and related policies, which may be manipulated by incumbent governments to encourage voter support[10]. As the business activities and the credit profiles of FIs are particular sensitive to fiscal and monetary policies it is necessary to control for political business cycles in estimating a FIs' migration probability. This study extends the literature by exploring whether and how being in a presidential election year affects the rating migration dynamics of FIs.

3. Method

3.1. Estimation approach

A rating state begins when a FI enters a rating grade after the start of the study and ends when the FI migrates to another grade, withdraws from being rated, or the study period ends. The survival time (survival duration) of each rating state is the time the FI maintains the same grade. If a FI experiences a migration event of interest during the study period, it is regarded as an event observation. If a FI leaves the study due to rating withdrawal or any other reason apart from a migration event of interest, its survival time is treated as censored. Rating states starting prior to the commencement of the observation period or ending after the observation period are also regarded as censored.

The data includes FIs which pass the screening test of having experienced at least two prior rating migrations. This ensures that there is a rating history for each FI examined. A FI may contribute several rating states to the dataset which may lead to dependence among

[10] See, for example, Beck (1987), Grier (1989), Haynes and Stone (1989, 1990, 1994), Klein (1996)

observations. This problem is minimised in two ways . First, the covariates in the models control for dependence. Second, the study uses the marginal-event specific method proposed by Wei, Lin, Weissfeld (1989) to account for dependence among rating states of the same FI.

The estimation procedure uses risk sets composed of all the rating observations that are at risk of a migration event at time *t*. In estimating a model for downgrades/ upgrades a new risk set is formed at each time *t* when a migration event of interest occurs. Observations leave the risk set once they experience an event of interest, or when they are censored. In forming the risk sets for the downgrade (upgrade) model, downgrades (upgrades) will be treated as events and upgrades (downgrades) will be treated as censored.

Three Cox's hazard models, a proportional model and two dynamic models, were developed for this study. The proportional Cox's hazard model (Cox, 1972) includes 3 time-independent covariates capturing several aspects of the current rating. The proportional model explores the effects of the current rating on the probability of a rating migration without controlling for issuer-heterogeneity (rating history, industry sub-sector) and time-heterogeneity (macro-economic conditions, political business cycle). The base and the extended dynamic models incorporate the same set of 6 time-varying covariates capturing macro-economic conditions and political business cycle, and the same set of 19 time-independent covariates describing the rating history and the sub-sector of each rating observation. The difference between the two dynamic models is the presence of time-independent current rating covariates. The base dynamic model explores the impact of issuer-heterogeneity and time-heterogeneity on the hazard of a migration in the absence of the current rating. The extended dynamic model additionally includes 3 time-independent current rating covariates, and examines whether the issuer-dependence and time-dependence properties persist.

3.2. Estimation model

The proportional Cox's hazard model (Cox, 1972) for state *m* can be expressed as:

$$h_m(t,Z) \;=\; h_{(0)}(t)\;\exp[Z_{\mathrm{j}}^{\mathrm{m}}\beta_{\mathrm{j}}] \tag{1}$$

Where: $h_m(t, Z)$ is state *m*'s migration hazard at time *t* given its time-independent covariate vector Z_j^m. $h_{(0)}(t)$ is the baseline hazard at time *t*, which is the hazard with the covariate vector set to zero. β_j is the vector of estimated coefficients for time-independent covariates Z_j^m.

The dynamic Cox's hazard models for rating state *m* at time *t* can be expressed as:

$$h_m(t,Z,Z(t)) \;=\; h_{(0)}(t)\;\exp[Z_{\mathrm{j}}^{\mathrm{m}}\beta_{\mathrm{j}}+Z_p^m(\mathrm{t})\beta_{\mathrm{p}}\;] \tag{2}$$

Where: $h_m(t, Z, Z(t))$ is state *m*'s migration hazard at time *t* given its time-independent covariate vector Z_j^m and its time-varying covariate vector $Z_p^m(t)$. $h_{(0)}(t)$ is the baseline hazard at time *t*. β_p is the vector of estimated coefficients for time-varying covariates $Z_p^m(t)$. β_j is the vector of estimated coefficients for time-independent covariates Z_j^m. Time-independent covariates Z_j^m have the values measured at the beginning of rating state *m* without being subsequently updated. Time-varying covariates $Z_p^m(t)$ have the values updated monthly over the survival time rating state *m* retains its current rating grade.

The likelihood $L_{t_m}^m$ that state *m* experiences a migration event at time t_m is calculated as state *m*'s hazard divided by the sum of the hazards of all rating observations in the risk set formed at event time t_m, $R(t_m)$.

$$L_{t_m}^m = \frac{\exp\left(\beta_j Z_j^m + \beta_p Z_p^m(t_m)\right)}{\sum\limits_{i\in R(t_m)} \exp\left(\beta_j Z_j^i + \beta_p Z_p^i(t_m)\right)} \tag{3}$$

Where: i represents a rating observation in the risk set formed at time t_m , $R(t_m)$.

The time-varying covariate value $Z_p^m(t_m)$ used in the estimation process was updated to the most recent monthly value as a migration event of interest occurred. Rating observation i appearing in different risk sets $R(t)$ will carry different values of the time-varying covariates $Z_p^i(t)$ updated at various event times t when those risk sets were formed.

Taking the product of the likelihoods, for all migrated states m, across all migration times t_m observed in the estimation sample gives the partial likelihood, PL, as follow:

$$PL = \prod_{m=1}^{n} L_{t_m}^m = \prod_{m=1}^{n} \left[\frac{\exp\left(\beta_j Z_j^m + \beta_p Z_p^m(t_m)\right)}{\sum_{i \in R(t_m)} \exp\left(\beta_j Z_j^i + \beta_p Z_p^i(t_m)\right)} \right] \quad (4)$$

Where: n is the number of migration events observed in the estimation sample.

The vectors of the estimated coefficients $\hat{\beta}_p$ and $\hat{\beta}_j$ can be obtained by maximising the partial likelihood (Hosmer, Lemeshow, May, 2008, pp. 213-216).

As seen in equation (3), the baseline hazard $h_{(0)}(t)$ is not needed in the estimation process. However, it is required to estimate the hazard of a future event. In the presence of the time-varying covariates $Z_p(t)$ the proportionality assumption of the conventional Cox's hazard model (Cox, 1972) does not hold and the baseline hazard $h_{(0)}(t)$ can not be extracted from the Cox's regression results. Estimating the baseline hazard function $h_{(0)}(t)$ and forming the hazard of a future event from the dynamic Cox's hazard model with time-varying covariates is challenging.

This study uses the method proposed by Andersen (1992) and adopts the SAS codes published by Chen, Yen, Wu, Liao, Liou, Kuo, and Chen (2005) to estimate the integrated base line hazard. Given the vectors of the coefficients $\hat{\beta}_p$ and $\hat{\beta}_j$, the integrated baseline hazard $H_{(0)}(t)$ can be estimated as follow.

$$\hat{H}_{(0)}(t) = \sum_{t_m \le t} \frac{D_m}{\sum_{i \in R(t_m)} \exp\left(\hat{\beta}_j Z_j^i + \hat{\beta}_p Z_p^i(t_m)\right)} \tag{5}$$

Where: D_m is an indicator for whether the migration event occurred to state *m* at time t_m within the interval [0, t].

The integrated baseline hazard function $H_{(0)}(t)$ can also be estimated as a step function discontinued at event time t_m (Chen et al., 2005).

$$H_{(0)}(t) = \sum_{t_m \in t} [h_{(0)}(t_{m-1})(t_m - t_{m-1})] \tag{6}$$

The estimated baseline hazard function at time *t*, $\hat{h}_{(0)}(t)$, can then be derived from equations (5) and (6).

3.3. Probability survival estimates

At the start of a holdout rating state *q*, the subsequent migration time and the changes in macro-economic conditions over its survival duration are unknown. It is not possible to frequently update the values of the time-varying covariates $Z_p^q(t)$ over raring *q's* survival duration as only information up to the commencement of state *q* is available. The values of the time-varying covariates $Z_p^q(t)$ used to form time-varying survival forecasts for the holdout observation *q* were therefore measured at its beginning.

The estimated hazard for the holdout state *q* at time *t* can be estimated using its actual covariate vector Z_j^q and $Z_p^q(t)$, the estimated baseline hazard function $\hat{h}_{(0)}(t)$, and the estimated coefficient vector $\hat{\beta}_p$ and $\hat{\beta}_j$:

$$\hat{h}_q(t,Z,Z(t)) \ = \ \hat{h}_{(0)}(t) \ \exp[Z_j^q\hat{\beta}_j+Z_p^q(t)\hat{\beta}_p \ ] \qquad (7)$$

The predicted survival function of holdout state *q* at time *t* can be estimated as:

$$\hat{S}_q(t,Z,Z(t)) = \exp-[\sum \hat{h}_q(t,Z,Z(t))] \qquad (8)$$

3.4. Forecast evaluation

Survival probabilities estimated as in Equation (8) were used to sort holdout observations into two groups, survival and migration (downgrades in the downgrade model and upgrades in the upgrade model). The classification was then mapped with the actual migration outcome of each holdout rating state. A relevant question is what value will be used as a cut-off value to convert each probability estimate into a state estimate (migration/ survival)? Using the ROC curve removes the problem of identifying an optimal cut-off point as the entire range of possible cut-off points is considered. The ROC curve for each estimated model is determined by the hit rate and the false alarm rate, which respectively captures the model's ability in predicting migrated states correctly and survived states incorrectly. The area under the ROC curve reflects the ability of the estimated models to separate *ex ante* and rank rating state on whether the event of interest occurs or not. The ROC curve has been widely used to evaluate the discrimination power of credit risk models and rating systems[11]. It is employed to assess the discrimination ability of the estimated models out-of-sample.

3.5. Variables

The variables that capture issuer-heterogeneity and time-heterogeneity in rating migration dynamics were identified from the literature. The list of variables employed in this study and their definition are presented in Table 1.

[11] See, for example, Sobehart and Keenan (2001), Engelmann, Hayden and Tasche (2003), Basel Committee on Banking Supervision (2005), Tasche (2008)

TABLE 1 HERE

3.5.1. Time-independent variables

The rating data of FIs were obtained from Standard & Poor's CreditPro2010 issuer dataset. The data does not contain information on rating outlooks of issuers. A coding approach often used in the literature was adopted to replace Standard & Poor's alphabetical rating scales by numeric scales, varying from 0 to 21 with 0 being the default state (D) and 21 representing AAA rating[12]. Three sets of time-independent variables were constructed to capture the current rating, rating history and the sub-sector risk of each FI.

Three variables were created to capture the current rating state. *Start rating* describes the current rating level, *dummy investment boundary* and *dummy junk boundary* respectively indicate whether the current rating (*start rating)* is in the investment grade boundary (BBB+, BBB, BBB-) or speculative grade boundary (BB+, BB, BB-). These two dummies capture any non-linearity in the rating scales surrounding the investment/ speculative threshold.

Fifteen variables were created to capture various aspects of past rating behaviors such as rating age (*age since first rated),* the first rating received *(original rating),* the directions of lagged rating changes (*dummy lag1 down, dummy lag2 down)* the durations of lagged rating states *(lag one, lag two),* prior rating levels (*previous rating1, previous rating2),* upgrade and downgrade volatility *(rate prior up, rate prior down),* the occurrence of a fallen angel/ a rising star event (*dummy fallen angel, dummy rising star),* the incidence of a substantial rating jump (*dummy big down, dummy big up)* and a rating withdrawal (*dummy Not rated*).

The sub-sector of a FI is categorised by Standard & Poor's. Four dummies were created to capture sub-sector effects. The four major sub-sectors include *bank, holding bank company,*

[12] This coding approach has been widely adopted (Sy, 2002; Kim and Wu, 2008; Al-Sakka and Gwilym, 2009; Hill, Brooks, Faff, 2010). The numeric rating scale maintains the rank order of the alphabetical scale, captures fine revisions intra-rating, and allows for a compact presentation of the results.

finance company, and *saving and loan company*. FIs of these sub-sectors account for 84.7 percent of the upgrades and 81.3 percent of the downgrades observed in the study. FIs of other sub-sectors such as fund, brokerage company, financial service company, mortgage institution, asset manager, credit union, etc. contribute the remaining migrations to the study.

3.5.2. Time-varying variables

Six time-varying variables were created to account for macro-economic conditions[13] and the political business cycle. *Dummy NBER recession* captures the state of the economy. *Inflation* and *Industrial Production Growth* control for the general level of economic activity. *Term Structure Slope* reflects credit conditions and captures the future prospects of the economy (Estrella and Hardouvelis, 1991). *Russell 2000 Index Return* represents the performance of the stock market. *Dummy presidential election year* accounts for political business cycles.

As macro-economic conditions tend to affect the rating dynamics of FIs with a lag, an exponentially weighted average of lagged observations computed monthly over a window of 18 months was applied to construct macro variables other than dummies. The construction of macro-economic lagged values is similar to the approach applied by Figlewski et al. (2008). *Dummy NBER recession* and *Dummy presidential election year* were updated monthly and entered the dynamic models without any transformation.

4. Data

4.1. Estimation and holdout periods

The study covers the long period from January 1984[14] to March 2010, and thereby includes several different business cycles in the U.S. economy. The estimation period 1 January 1984-

[13] Twenty candidate macro-economic variables were considered and those that showed strong multicolliniarity were eliminated, leaving five macro-economic variables which were used in the dynamic models.

[14] As all macro-economic data was not available prior to 1982 and the macro-economic variables used were constructed in the form of 18 months of distributed lags, 1984 was chosen as the year of commencement.

31 December 2004 saw two economic recessions[15] (July 1990-March 1991, March 2001-November 2001), the U.S. stock market crash in 1987, the Mexican currency crisis in 1994, the Asian financial crisis in 1997, the Russian sovereign bond default in 1998, the collapse of the Long-Term Capital Market Hedge Fund in 1998, the dot-com bubble burst in 2000, the devastating 9/11 terrorist attack in 2001, the U.S. bond crisis in 2002-2003 and the dramatic bankruptcies of fallen angels like WorldCom and Enron. The period after the estimation period, 1 January 2005-31 March 2010 was used to construct a holdout sample for model validation purpose. This period witnessed the sub-prime mortgage crisis in 2007-2008, a prolonged economic recession from December 2007 to June 2009 and the unprecedented bankruptcies of a number of investment-grade rated FIs.

The time series for the exponentially weighted average of macro-economic variables used in this study are shown in Figure 1. The holdout period January 2005-March 2010 saw substantial deteriorations in macro-economic conditions. Additional analysis (not reported) indicates that the statistics of macro-economic variables for the estimation and the holdout periods are statistically different (except *Term structure slope).*

FIGURE 1 HERE

4.2. Rating profiles

The estimation and the holdout sample include 884 and 399 rating observations, respectively, excluding observations not passing the screening test of experiencing at least two prior migrations. Of the 884 estimation observations, 407 experienced downgrades and 220 experienced upgrades. Of the 399 holdout observations, downgrades and upgrades respectively contribute 223 and 48 states. The number of downgrades (upgrades) that

[15] The start and end date of economic recessions in the U.S. were provided by the National Bureau of Economic Research (http://www.nber.org/)

occurred in the five-year holdout period is equivalent to 55 percent (22 percent) of the respective incidences observed during the 21-year estimation period.

The descriptive statistics of rating variables for observations in the estimation and the holdout samples are given in Table 2.

TABLE 2 HERE

Additional analysis (not reported) shows that some aspects of rating history for observations in the estimation and in the holdout samples have a statistically different mean/ median. These include rating age (*age since first rated),* the first rating *(original rating),* the duration and the direction of lag two rating state (*lag two, dummy lag2 down),* the occurrence of a rating withdrawal *(dummy Not rated),* the incidence of a substantial upgrade *(dummy big up),* and rating volatility (*rate prior up, rate prior down).*

4.3. Migration propensities

The proportion of downgrades rises from 46 percent in the estimation period to 55.89 percent in the holdout period whereas the proportion of upgrades dropped sharply from 24.89 percent to 12.03 percent over these two periods. Additional statistics (not reported) show that the proportions of downgrades/ upgrades in the estimation and holdout period are statistically different.

The distribution of rating migrations across rating grades (*start rating)* in the estimation and holdout periods are depicted in Figure 2.

FIGURE 2 HERE

Additional analysis (not reported) indicates that both down states and up states in the study have the mean/ the median *start rating* located in the speculative/ investment grade threshold. Figure 2 Panel A shows that 36.4 percent of the downgrades and 51.4 percent of the upgrades observed in the estimation period are from boundary ratings. The holdout period also contains a concentration of migrations from the boundary ratings (Figure 2 Panel B). In both periods, migrations from the investment threshold ratings (BBB-, BBB, BBB+) far exceed migrations from speculative threshold grades (BB-, BB, BB+).

Both upgrades and downgrades in the estimation period are heavily concentrated at low investment ratings varying from BBB- to A+. Only 12.5 percent of downgrades and 1.8 percent of upgrades are observed at investment ratings above A+ (Figure 2 Panel A). However, there is a shift towards higher *start rating* for both down states and up states in the holdout period. As depicted in Figure 2 Panel B, 22.9 percent of downgrades and 20.8 percent of upgrades are concentrated in upper investment ratings, varying from AA- to AAA.

Both the estimation and holdout samples show a dominance of migrations in the investment rating region. 63 percent of the downgrades and 72 percents of the upgrades observed in the estimation period are from investment rating territory. A similar concentration of migrations in the investment rating spectrum was observed in the holdout period. This is not surprising as an investment grade rating is the norm in the financial institution sector.

Consistent with Altman and Kao (1991), Lucas and Lonski (1992), Lando and Skodeberg (2002), it was found that rating volatility increased over time, with downgrades dominating upgrades. The ratio of downgrades to upgrades increased sharply from 185 percent in the estimation period to 465 percent in the holdout period. Both investment ratings and speculative ratings deteriorated being more frequently downgraded than upgraded in recent years. Downgrades outnumbered upgrades by 62 percent and 146 percent for investment and speculative ratings in the estimation period. The holdout period showed a substantial increase in downgrade frequency, with downgrades surpassing upgrades by 303 percent and 550 percent for investment and speculative ratings respectively. The elevated rating volatility in the holdout period can partly be attributed to CRAs' excessive pessimism in revising ratings downward and a reluctance to revise ratings upwards during an economic downturn (Amato and Furfine, 2003).

4.4. Time to events (survival time)

The histogram of time to upgrades and time to downgrades (survival time) for rating states in the estimation and in the holdout periods are depicted in Figure 3. Up states and down states both show positively skewed distributions. Down states have a markedly shorter survival time than up states and heavily mass in durations shorter than a year. There is a shift to shorter survival time for both up states and down states in the holdout period (Figure 3 Panel B).

FIGURE 3 HERE

The descriptive statistics of the survival time for rating states in the study are given in Table 3. Additional analysis (not reported) indicates that down states/ up states in the estimation and holdout periods have statistically different survival time. It takes about half of the time for a migration to occur in the holdout period than it does in the estimation period. This is to be expected as CRAs exhibit a propensity to over-react to an economic recession and have also tended to be quicker to revise ratings downward in recent years (Altman and Kao, 1991).

TABLE 3 HERE

Overall, relative to rating states in the estimation period, those in the holdout period had different rating profiles, experienced shorter survival times and intensified rating volatility with downgrades substantially surpassing upgrades.

5. Results

5.1. Estimation results

The proportional model was estimated as in Equation (1), the base and extended dynamic models were estimated as in Equation (2). The estimation results of three models for downgrades and upgrades are given in Panel A – Table 4. Panel B – Table 4 summarizes the number of events and censored observations categorised by sub-sectors in the estimation sample. Panel C– Table 4 provides the statistics on the goodness of fit of the models.

TABLE 4 HERE

In estimating a parsimonious model the backward stepwise estimation procedure was used. Variables were retained according to the log-likelihood ratio test, at the 10 percent level or better, derived from the maximum likelihood procedure used to estimate the models. All retained variables were significant at the 10 percent level or better based on a Wald chi-square test. The following discussion focuses on the significant variables present in the models.

5.1.1. Proportional model

As shown in Panel A Table 4 (columns 2-7), the effect of *start rating* is the same for upgrades and downgrades. A higher *start rating* raises the probability that the current rating state continues. Consistent with Carty and Fons (1993) and Carty (1997), it is found that issuers on the threshold of investment grades (*dummy investment boundary)* have a strong incentive to retain investment grade status. They are 54 percent more likely to ascend to higher rating grades and 18 percent less likely to become a fallen angel. This suggests that some aspects of a current rating affect the probability of a subsequent migration. The next question to be addressed is whether or not the migration dynamics of FIs exhibit issuer and time heterogeneity?

5.1.2. Base dynamic models

As shown by Panel A Table 4 (columns 8-13), the migration hazard of a FI, without controlling for the current rating, depends significantly upon rating history, macro-economic factors and the political business cycle. The source of issuer-heterogeneity in the rating dynamics of FIs can be entirely attributed to several aspects of rating history. The models for upgrades and downgrades have only one rating history variable in common, which is *previous rating1*. The higher the rating of lagged one state, the more likely the current rating persists.

The upgrade dynamics exhibit less dependence on rating history and few variables are significant. A higher original rating (*original rating)* makes a FI more likely to be upgraded but the effect is small compared to the effect of the prior rating level (*previous rating1*) and lagged rating duration (*lag two)*. Increasing the duration of lagged two rating state (*lag two)* by one year raises the probability the current rating persists by 11.3 percent, which is consistent with the evidence of duration dependence in corporate rating dynamics (Lando and Skodeberg, 2002).

The downgrade model features more significant rating history variables, some with particularly large coefficients. The ratings of lagged one and lagged two states (*previous rating1, previous rating2*) are significant but their signs are reversed. Downgrades exhibit duration dependence and downward momentum but lagged rating duration (*lag one*) has a much smaller effect than the direction of lagged rating change (*dummy lag1 down)*. A one year increase in lagged one duration (*lag one*) makes the current rating state 7.7 percent more likely to continue. In contrast, a downgrade at lagged one state (*dummy lag1 down)* makes a subsequent downgrade 286 percent more likely. The occurrence of a substantial jump to higher rating grades (*dummy big up)* also has a strong impact, raising the probability of a rating bounce by 54 percent.

The source of time-heterogeneity in the rating dynamics of FIs can be attributed to macro-economic conditions and political business cycles. The models for upgrades and downgrades have several macro-economic variables in common but their signs are reversed. FIs are more likely to be upgraded and less likely to be downgraded in periods characterised by a high *industrial production growth*, a steep yield curve (*term structure slope)* and a stock market boom (*Russell 2000 Index Return*). *Industrial production growth* has a strong impact for upgrades; a one percent increase leads to a 186 percent higher upgrade probability. *Inflation* is only significant in the downgrade model and its effect is substantial. An increase of 1 percent makes a subsequent downgrade 439 percent more likely.

Of particular interest, in contrast to Nickell et al. (2000) and Bangia et al. (2002), it was found that the ratings of FIs do not move pro-cyclically. FIs operate in a highly regulated business environment and are subject to strict controls regarding capital adequacy and loss reserves. Most FIs have a strong credit profile and receive investment grade ratings. Those rated in the speculative grades tend to be weeded out and acquired by other institutions (Lando and Skodeberg, 2002). As shown in Figure 2, the investment rating spectrum contributes the majority of migrations observed during the study. Amato and Furfine (2003) suggest that issuers with high ratings are less sensitive to macro-economic conditions than those with low ratings. FIs tend to perform well towards the end of a recession when demand for credit and lending activity increase in anticipation of recovery. It is therefore not surprising that FIs are 42.3 percent less likely to be downgraded during economic recessions (*dummy NBER recession).*

The rating dynamics of FIs also depend on political business cycles. Being in a year when a presidential election (*Dummy presidential election year*) occurs reduces the probability of an upgrade by 23.4 percent. Election years are characterised by uncertainties in the outcome of the election and election-related manipulations of fiscal/ monetary policies. As FIs are particularly vulnerable to political risk and changes in fiscal/ monetary policies, it is to be expected that CRAs are more reluctant to revise a FI's ratings upward during an election year.

The above suggests that rating history, macro-economic conditions and the political business cycle jointly, and often severely, have a strong impact on the probability of a rating change. The question then arises whether their impact remains intact in the presence of the current rating?

5.1.3. Extended dynamic model

As shown in Panel A Table 4 (columns 8-13 and 14-19), variables that are significant in the base models remain so in the extended model, mostly with the same sign. With regard to the significant macro-economic and political business cycle variables, the results of the extended dynamic models are consistent with the results of the base dynamic models. The effects of current rating and rating history variables generally correspond to the effects seen in the proportional/ base dynamic models. Upgrades show more dependence on rating history than downgrades after controlling for the current rating. Both upgrades and downgrades exhibit duration dependence (*lag one, lag two)* and downgrades show strong downward momentum (*dummy lag1 down)*. Despite these similarities there are marked differences between the extended model and the proportional/ base model. Notable changes are the presences of additional significant current rating and rating history variables in the upgrade model.

Controlling for issuer-heterogeneity and time-heterogeneity weakens the effect of the current rating on downgrades and strengthens its effect on upgrades. *Start rating* is no longer significant in the downgrade model whereas *Dummy junk boundary* appears in the upgrade model. Being rated in the boundary of investment/ speculative grades (*dummy investment boundary, dummy junk boundary)* makes an upgrade more likely. This is consistent with previous studies.

The extended model for upgrades features a greater number of rating history variables. *Dummy lag1 down*, *dummy fallen angel*, *dummy big up*, and *dummy Not rated* become significant. A downgrade at lagged one state (d*ummy lag1 down)* and a fallen angel event (*dummy fallen angel*) reduce the probability of an upgrade whereas a prior substantial upgrade (*dummy big up*) and a prior rating withdrawal (*dummy Not rated*) make an upgrade more likely. The distinguishing feature lies in the substantial effect of *dummy Not rated.* A break in the rating history by being unrated (*dummy Not rated*) raises the probability of an upgrade by

506 percent. This suggests that issuers who withdrew from being rated tend to choose to be re-rated when they are likely to receive better credit ratings.

The coefficient sign of lagged one rating (*previous rating1)* reverses after controlling for the current rating. For both downgrades and upgrades, the significant rating levels of the two recent rating states have reverse coefficient signs. The most recent rating has a stronger effect than the immediately preceding rating. For example, *previous rating1* dominates *previous rating2* in the downgrade model whereas *start rating* dominates *previous rating1* in the upgrade model. An improvement in the rating of the most recent state (*start rating* for upgrades and *previous rating1* for downgrades*)* raises the probability that the current rating continues.

The extended models for upgrades and downgrades feature several common rating variables (*dummy investment boundary, previous rating1, dummy lag1 down, dummy big up);* however, their signs are often reversed. This suggests that downgrades and upgrades exhibit different issuer-heterogeneity. Being on the investment grade boundary (*dummy investment boundary*) and having a higher lagged one rating (*previous rating1)* makes an upgrade more likely and a downgrade less likely. In contrast, a downgrade at lag one state (*dummy lag1 down)* leads to a substantial higher downgrade risk and a lower upgrade hazard. This is consistent with the evidence of rating drift in corporate rating dynamics.

A substantial jump to higher grades (*dummy big up)* raises the hazard of a subsequent migration; the effect is the same for upgrades and downgrades. This reflects different situations that are associated with a multiple-notch upgrade. If the jump is in response to an "unusual sensitivity to credit quality of a particular occurrence" (Standard & Poor's, 2001) it makes a subsequent rating bounce more likely as most issuers attain an "average rating" under normal circumstances (Kavvathas, 2001, pp. 32-33) and ratings tend to migrate toward the middle of the rating spectrum (Altman and Kao, 1992b, p. 70). However, if a celebrated upgrade merely represents a partial revision to a substantial improvement in the credit quality of an issuer, the jump raises the probability of a subsequent upgrade. Ratings tend to change in a predictable fashion (Hamilton and Cantor, 2004) and CRAs tend to avoid costly frequent reversals (Loffler, 2005).

The strong effect of rating history, macro-economic conditions and the political business cycle are reinforced after controlling for the current rating. The next question addressed is whether the evidence of issuer-heterogeneity and time-heterogeneity, discussed above, persists after taking into account several situations underlying rating withdrawals?

5.2. Sensitivity analysis against informative censoring

Rating withdrawal accounts for 16.74 percent of the estimation sample and 13.78 percent of the holdout sample. Issuers withdrawing from being rated are treated as censored observations. If the reason a censored rating state leaves the study is not independent of the migration event, this type of censoring may lead to informative censoring and introduce bias into parameter estimates. For example, an issuer of deteriorating credit quality may choose to be unrated to bypass CRAs and decide to be re-rated when its credit quality improves.

There is no statistical test to check for, and no standard method to deal with informative censoring (Allison, 1995, p. 14). Two sensitivity tests based on the two assumptions underlying a high risk and a low risk scenario can be used to examine the effect of informative censoring (Allison, 1995, pp. 249-252). The high risk scenario assumes that censored issuers of deteriorating credit quality would be downgraded immediately after leaving the study whereas the low risk scenario assumes that they would have retained their current rating as long as any other issuer. The sensitivity tests were applied to the proportion model, the base and the extended dynamic models for downgrades. For the sake of brevity, the detailed results are not displayed. It was found that treating 148 unrated rating states in the estimation sample as either non-informative censored (low risk scenario) or non-censored (high risk scenario) does not substantively alter the main results of the base scenario. In any scenario, downgrades exhibit strong dependence on rating history and macro-economic factors. These key determinants can therefore be used to forecast future migrations, but how accurate are such forecasts?

5.3. Predictive forecast assessment

5.3.1. Forecast horizon

Survival probabilities were estimated as in Equation (8) for rating states in the holdout sample at different forecast horizons t. The selection of the horizon t depends on the rating migration forecast objectives. Portfolio models generally use a one-year forecast horizon to calculate credit risk exposures and this horizon is also appropriate to determine regulatory capital requirements for banks (Altman, 1998). In practice CRAs publish a rating transition matrix with a one-year horizon. The one-year horizon also matches the migration propensity observed during the study. As depicted in Figure 3 Panel B, down states (up states) in the holdout sample mass at survival durations shorter than one year (two years). This study therefore generates survival probability estimates for holdout observations at yearly intervals over the two-year forecast horizon.

5.3.2. Forecast performance

Figure 4 depicts the time-varying survival forecasts formed by the base dynamic downgrade model for four holdout FIs. The actual survival/ migration outcome of each FI was recorded and mapped with the survival estimates. As shown in Figure 4, downgrade and rating withdrawal “candidates” were assigned survival probabilities that sharply decline over time whereas the survival “candidate” was placed in the upper survival probability category across all forecast horizons.

FIGURE 4 HERE

The areas under the ROC curves (AUROC) for one-year and two-year survival forecasts generated by the estimated models are summarised in Table 5. A model forming random estimates has an AUROC of 50 percent. The higher the AUROC, the more discriminative the estimated model is in generating survival estimates.

TABLE 5 HERE.

As shown in Table 5, the proportional models perform poorly in distinguishing states that survived from states that migrated within a two-year forecast horizon. This poor forecast performance of the current rating contrasts with the finding that the time-homogeneous Markov property adequately holds within a one or two-year horizon (Kiefer and Larson, 2007; Frydman and Schuermann, 2008).

The base dynamic model performs well (modestly) in discriminating survived states from downgraded states at a one-year (two-year) horizon. Generating survival estimates for holdout states, particularly down states, is challenging as the estimation period is not representative of the holdout period. Downgrades escalated, were more rapid and intensified in the holdout period. The mean survival time for holdout down states was 0.73 years, about half of the mean survival time for their estimation peers (Table 3). More than 75 percent of holdout down states masses at survival durations less than a year (Figure 3 Panel B). The use of time-varying covariates in the dynamic model accounts for changes in the macro-economic conditions which resulted in a rapid deterioration in the credit quality of holdout FIs. The dynamic model therefore captures the acceleration of downgrades in the holdout period.

The base dynamic model for upgrades merely exhibits modest discriminatory power at the one-year horizon and performs comparable to a random model at the two-year horizon. The employment of time-varying covariates does not give the upgrade model a significant information advantage for two reasons. First, upgrades are less dependent on common systematic risk factors than downgrades (Koopman et al., 2006). Second, CRAs devote more resources to detecting deterioration in the credit quality of an issuer than to identifying any improvement in its credit profile. Downgrade “candidates” are generally under the close scrutiny of CRAs and subject to short credit review cycles whereas upgrade “candidates” are less often reviewed by CRAs. Consequently, downgrades are rapid whereas upgrades tend to lag the improvement in the credit quality.

As shown by Table 5, the extended models have similar AUROCs as the base models. Adding the current rating does not improve the discriminatory ability of the dynamic models. Information provided by the current rating appears to be “incremental” compared with information contained in rating history, macro-economic factors and political business cycle. The presence of additional significant rating history variables, for example *dummy Not rated,* does not give the extended upgrade model an edge as observations in the estimation and in the holdout samples have statistically different rating withdrawal profiles (Table 2).

The deterioration in the discrimination ability of both downgrade and upgrade models at two-year horizon suggests that the information contained in the static values used to form estimates for holdout observations become increasingly stale as the forecast horizon extends.

6. Conclusion

The study used Standard & Poor’s issuer rating data to examine the rating dynamics of FIs in the U.S. over the period January 1984 to March 2010. It was found that some aspects of the current rating affect future rating changes. Downgrades and upgrades exhibit strong but markedly different issuer-dependence and time-dependence. The sources of issuer-heterogeneity can be attributed to several aspects of rating history whereas the sources of time-heterogeneity can be attributed to macro-economic conditions and the political business cycle. Evidence for the above is reinforced after controlling for the current rating.

Future rating migrations are strongly dependent on rating history and some historical aspects persist. A longer lagged rating duration leads to a longer current rating duration. A downgrade at lag one state makes a subsequent downgrade 280 percent more likely. Different rating routes result in different rating distributions and path-dependence is more pronounced in the presence of the current rating. A fallen angel is less likely to ascend the rating spectrum whereas a prior rating withdrawal raises the upgrade probability by more than 500 percent.

The study provides substantial new evidence for time-heterogeneity in FIs' rating dynamics. Upgrades are less likely to occur in presidential election years. Downgrades are more frequently observed during inflationary periods but less often seen in recessions. Periods of high industrial production growth, steep yield curve, and bull stock market observe more upward and less downward revisions.

The ROC curve was used to test the discrimination ability of the survival probability estimates formed by the estimated models for holdout observations at one- and two-year horizons. The forecast performance of the current rating is disappointing. Issuer-heterogeneity and time-heterogeneity, however, exhibit some predictive accuracy. A large proportion of holdout FIs that subsequently downgraded were flagged as downgrade "candidates" in a year prior to their migrations. Controlling for the current rating does not improve the predictive accuracy of the dynamic downgrade and upgrade models. This suggests that the value of information contained in the current rating is small compared to the information value provided by rating history and macro-economic factors.

The results of this study are limited due to the rating data used, which does not include the rating outlook of each issuer. The assessment of forecast accuracy suggests several directions in which the study may be extended. One possibility is to incorporate rating outlook as a time-varying covariate which may improve the predictive accuracy of the dynamic model (Vazza, Leung, Alsati, and Katz, 2005). Another possibility is to update the model using a moving window, or regularly update the time-varying covariates used to form estimates for holdout states. The use of dynamic data in the form of time-series forecasts for holdout states will control for the expected changes of macro-economic and political environment over the holdout period and will introduce a forward-looking perspective into the survival estimates. The study may also be extended by employing a proper scoring rule, such as the Brier score (Brier, 1950), to assess the forecast performance of the model. The Brier score can be decomposed into components of forecast accuracy (Winkler, 1996). The decomposition provides insight into the sources of forecast errors and useful feedback to improve the models.

This study is particularly relevant for banks and regulators in maintaining a sound risk management framework. Under the Basel II framework banks can associate each credit rating to a capital charge. The findings of this study imply that rating history, macro-economic conditions and the political business cycle signals information useful in determining loss reserves. Banks should therefore account for these risk factors in assessing the credit quality of, and assigning ratings to, their counterparties. The dynamic hazard model can be utilised to estimate time-varying rating migration matrices for counterparties from different sectors. The model provides banks with the ability to determine dynamic economic risk capital and to detect deterioration in the credit quality of investment portfolios with a sufficient lead time. The model may also aid regulators in monitoring FIs' time-varying survival profiles and identifying impaired FIs at an early stage.

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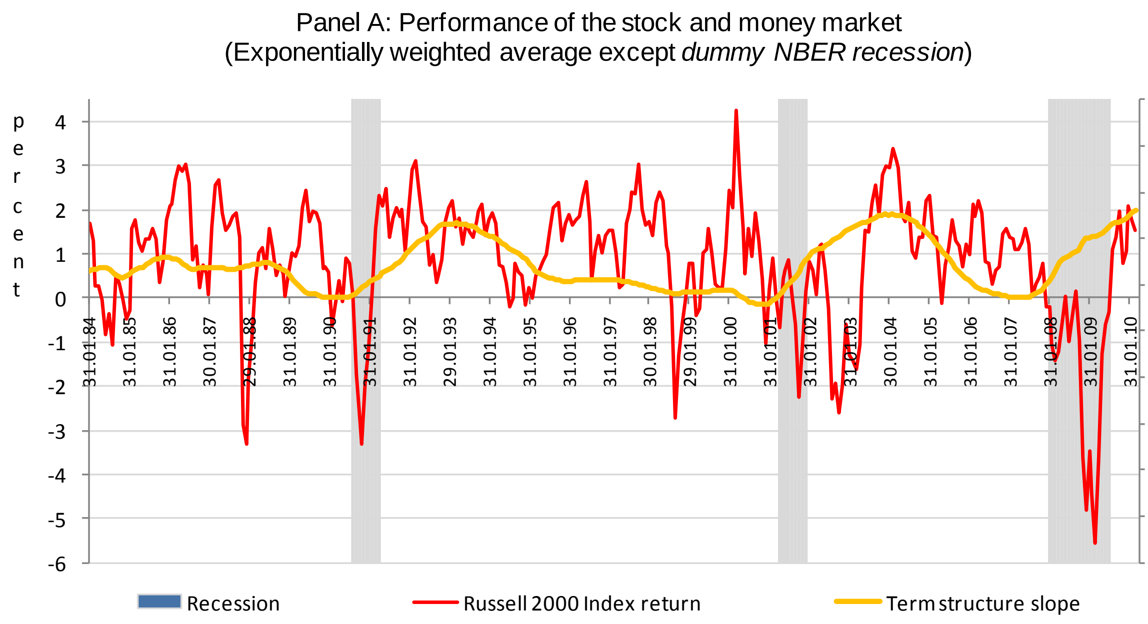
Fig. 1



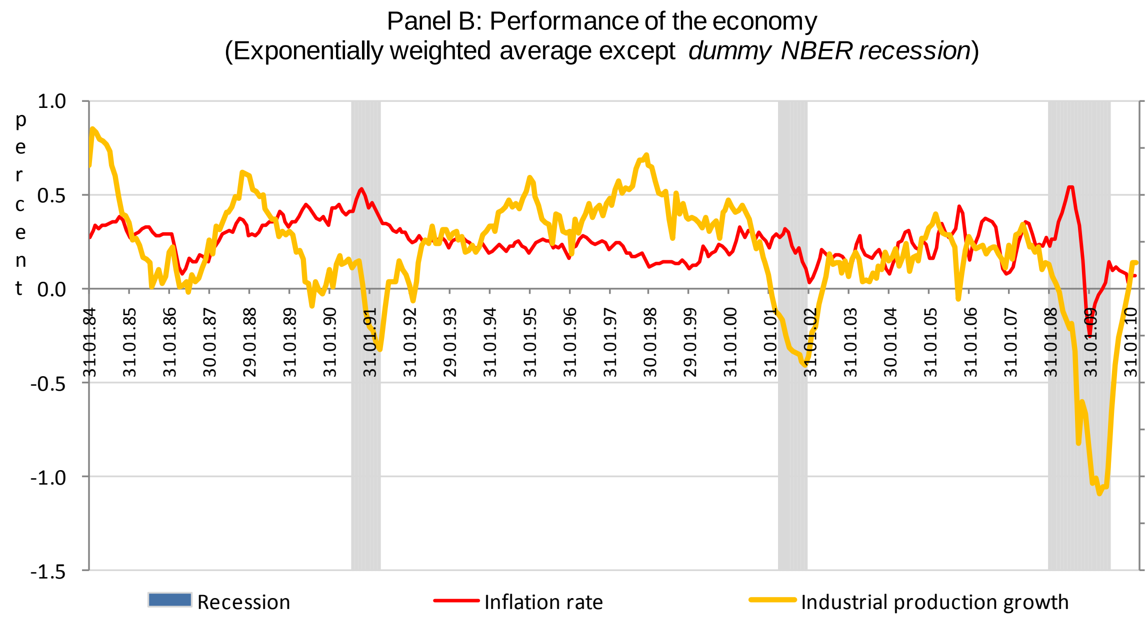


Figure 1 above depicts the time-series values of macro-economic variables employed in the study. Except *dummy NBER recession*, other macro-economic variables were constructed as exponentially weighted averages of lagged observations computed monthly over an 18-month window. The construction of lagged values is similar to Figlewski et al. (2008)'s approach. Except *Term structure slope*, the values of macro-economic variables in the estimation period (1984-2004) and in the holdout period (January 2005-March 2010) are statistically different.

Fig. 2

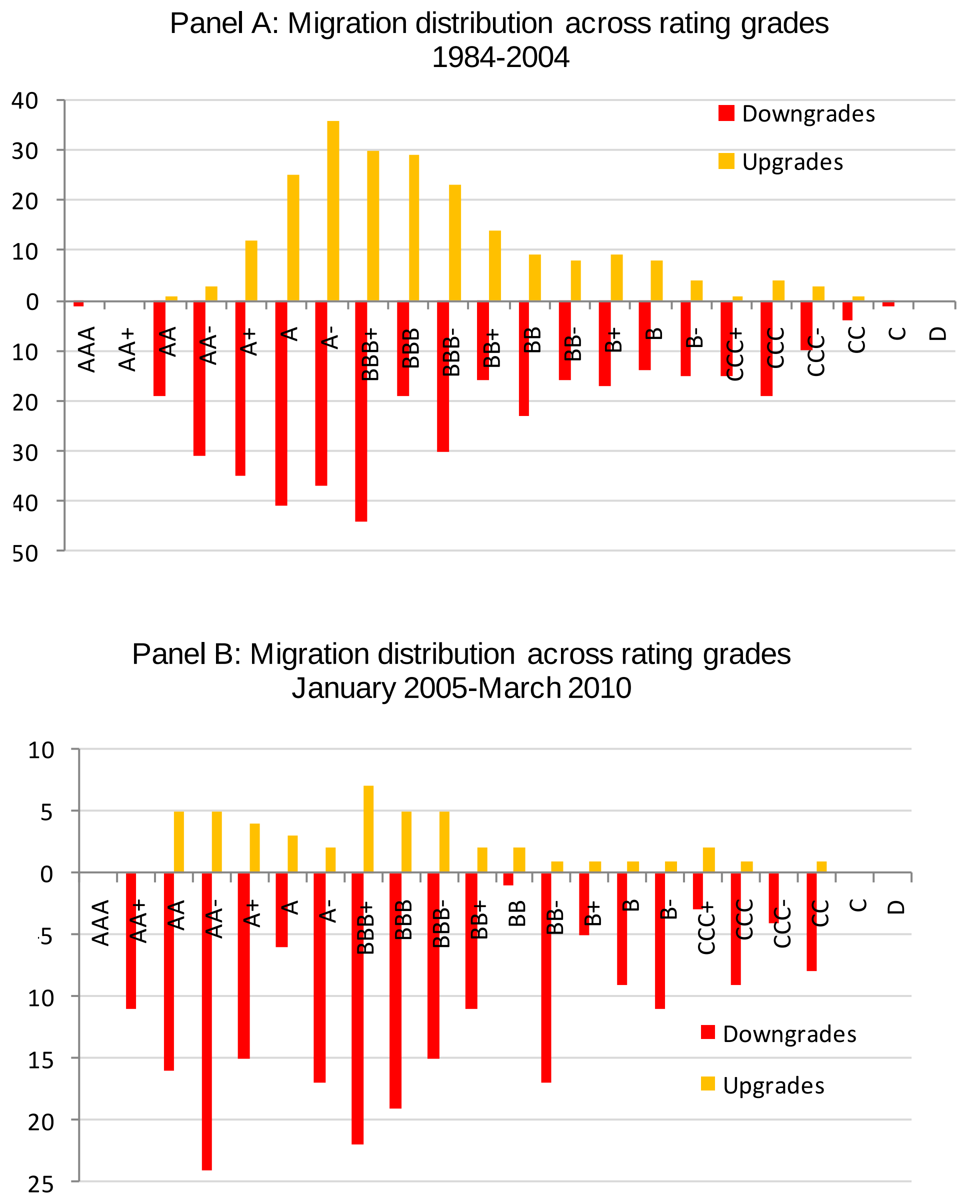
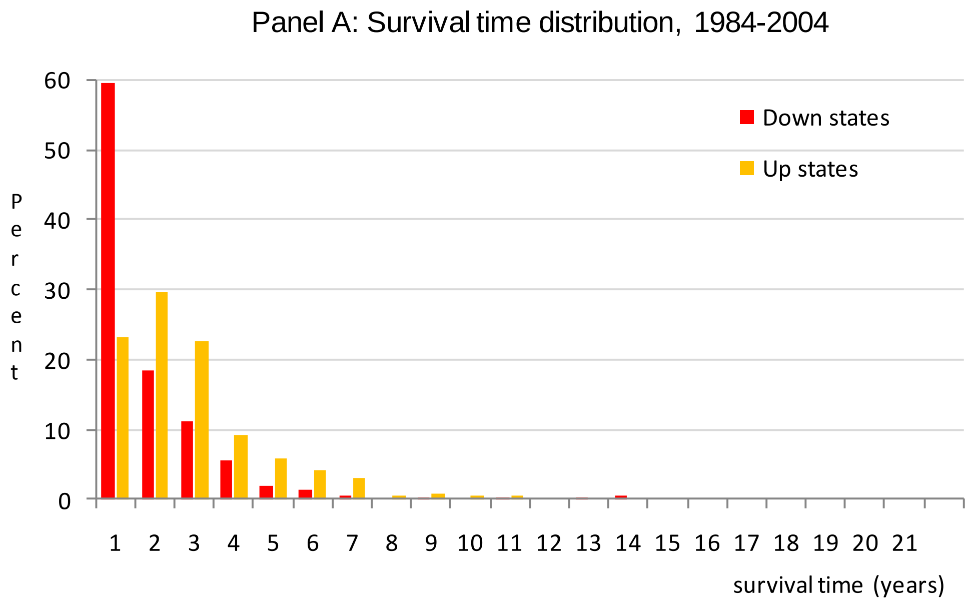


Figure 2 above depicts the distribution of migrations across rating grades (*start rating)* in the estimation period (1984-2004) and in the holdout period (January 2005-March 2010). Of 884 estimation rating states, 407 experience downgrades and 220 underwent upgrades. Of 399 holdout observations, downgrades and upgrades respectively account for 223 and 48 observations.

Fig. 3



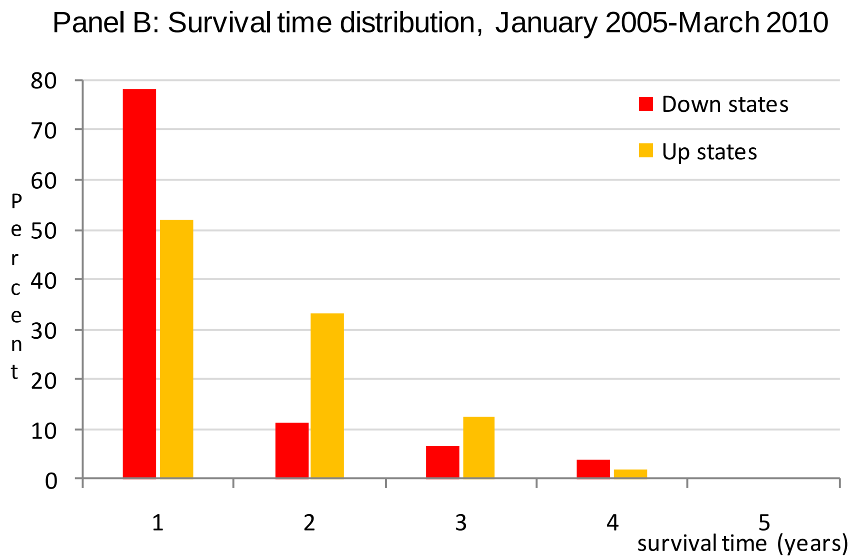


Figure 3 depict the survival time of down states and up states in the estimation and in the holdout period. The survival time of an observation is the length of time it retains its current rating grade measured from the time it enters a rating grade subsequent to the commencement of the study until the time it either migrates to another rating grade or becomes censored. A FI may contribute several rating states to the study. The estimation sample includes 407 down states and 220 up states, the holdout sample includes 223 down states and 48 up states.

Fig. 4

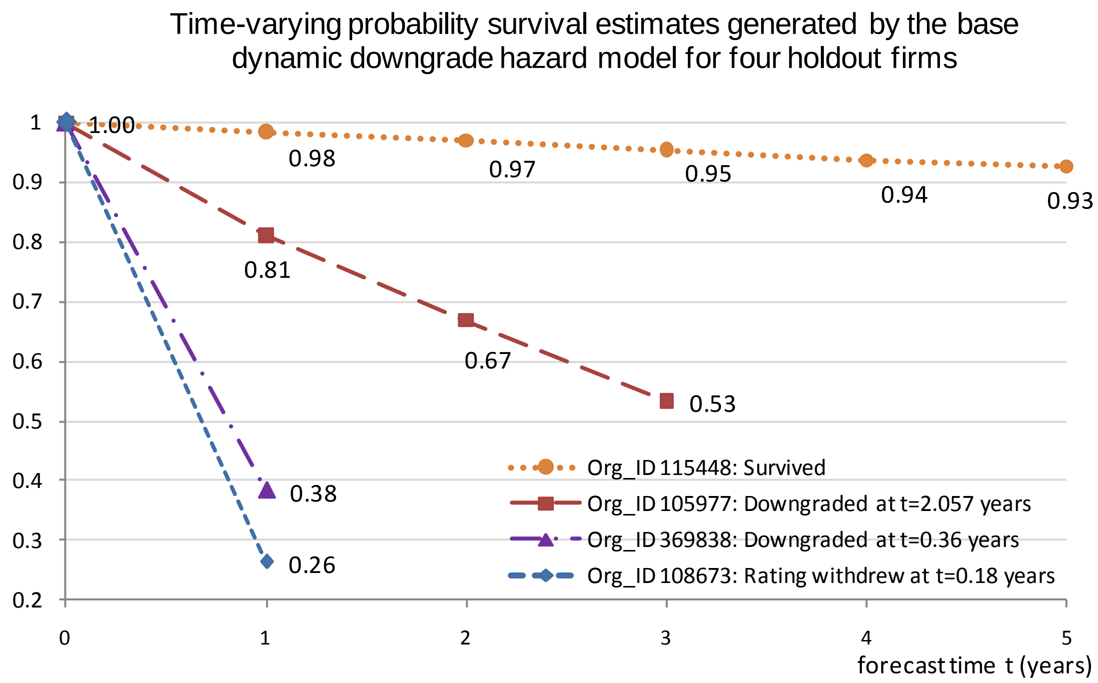


Figure 4 above depicts the time-varying probability survival forecasts estimated as in Equation (8) by the base dynamic downgrade hazard model for four holdout FIs. Each FI was assigned a unique organization identification number (Org_ID) by Standard & Poor's. The status of each FI was recorded and mapped with the survival estimates. Of the four holdout FIs examined, one survived, two downgraded, and one became unrated.

Table 1: Variable definition and references

Variables	Definition	References
Current rating		
Start rating	The rating at the commencement of the current rating state	Carty and Fons (1993), Carty (1997), Figlewski et al. (2008), Hamilton and Cantor (2004), Jorion, Shi, and Zhang (2005)
Dummy investment boundary	The dummy takes the value of one if the start rating is in the investment grade boundary, BBB-, BBB, BBB+, and zero otherwise	Carty and Fons (1993), Carty (1997), Johnson (2004), Livingston, Naranjo, Zhou (2008)
Dummy junk boundary	The dummy takes the value of one if the start rating is in the speculative grade boundary, BB-, BB, BB+, and zero otherwise	
Rating history		
Age since first rated	The length of time since the firm was first rated until the start of the current rating state	Altman and Kao (1991), Altman (1998), Figlewski et al. (2008)
Original rating	The rating of a firm when it was first rated	Altman and Kao (1991), Altman and Kao (1992a, 1992b), Jorion et al. (2005), Figlewski et al. (2008)
Lag one	The duration of the rating state that ended with either a downgrade or an upgrade and immediately preceded the current rating state	Carty and Fons (1993), Lando and Skodeberg (2002), Dang (2010)
Lag two	The duration of the rating state that ended with either a downgrade or an upgrade and immediately preceded the lag one rating state	
Previous rating1	The rating at the commencement of the lag one rating state	Bannier and Hirsch (2010)
Previous rating2	The rating at the commencement of the lag two rating state	
Dummy lag1 down	The dummy captures the direction of the lag one rating change and takes the value of one if the lag one rating ends with a downgrade, and zero otherwise	Carty and Fons (1993), Altman and Kao (1992a,1992b), Kavvathas (2001), Lando and Skodeberg (2002), Bangia et al. (2002), Hamilton and Cantor (2004), Mah and Verde (2004), Figlewski et al. (2008)
Dummy lag2 down	The dummy captures the direction of the lag two rating re-grade and takes the value of one if the lag two rating ends with a downgrade, and zero otherwise	
Dummy Not rated	The dummy takes the value of one if a firm underwent a break in rating history from its entry to the study until the beginning of the current rating state	Carty (1997), Dang (2010)

Table 1: Variable definition and references (cont.)

Variables	Definition	References
Rate prior up	This is the average number of upgrades per year over the firm's rating history. It is calculated as the number of upgrades observed between the entry of a firm to the study and the commencement of the current rating state divided by the duration from the time of entry until the start of the current rating state.	Altman and Kao (1991), Lucas and Lonski (1992), Lando and Skodeberg (2002), Koopman et al. (2006), Dang (2010)
Rate prior down	This is the average number of downgrades per year over the firm's rating history. It is calculated similar to *rate prior up* except that the numerator of the ratio is the number of downgrades observed from the time the firm entered the study until the inception of the current rating state	
Dummy Fallen Angel	The dummy takes the value of one if a firm experienced a fallen angel event (a downgrade from an investment-grade rated rating to a speculative-grade rated rating) from its entry to the study until the inception of the current rating state	Mann, Hamilton, Varma, and Cantor (2003), Vazza, Aurora, and Schneck (2005)
Dummy Rising Star	The dummy takes the value of one if a firm experienced a rising star event (an upgrade from a speculative-grade rated rating to an investment-grade rated rating) from its entry to the study until the beginning of the current rating state	Dang (2010)
Dummy big down	The dummy takes the value of one if a firm experienced a downgrade of at least three rating notches from its entry to the study until the commencement of the current rating state	Lucas and Lonski (1992), Standard and Poor's (2001), Dang (2010)
Dummy big up	The dummy takes the value of one if a firm experienced an upgrade of at least two rating notches from its entry to the study until the inception of the current rating state	
Sector dummies Dummy_Bank Dummy_Bank Holding Co. Dummy_Finance Co. Dummy_Saving and Loan Co.	Financial institutions were categorized into five major groups based on their sub-sectors given by Standard & Poor's. Four dummies were created to account for sub-sector effects. The sub-sector dummy takes a value of one if a financial institution is either a bank, a holding bank company, a finance company, or a saving and loan company, and zero otherwise. Financial institutions in the *other* group (brokerage companies, financial service companies, funds, mortgage institutions, credit unions, asset managers, etc.) were left uncoded.	Nickell et al. (2000), Kavvathas (2001), Lando and Skodeberg (2002), Kadem and Lenk (2008)

Table 1: Variable definition and references (cont.)

Variables	Definition	References
Macro-economic (time-varying)		
Dummy NBER recession	The dummy takes a value of one if the rating state starts at the time of an economic recession, defined by National Bureau of Economic Research (NBER)	Figlewski et al. (2008), Dang (2010),
Inflation (%)	The time series of percentage change in the seasonally adjusted Consumer Price Index were published by the U.S. Bureau of Labor Statistics	Figlewski et al. (2008)
Industrial production growth (%)	The time series of industrial production growth were published by the Federal Reserve Board of Governors	Figlewski et al. (2008), Dang (2010)
Term structure slope (%)	The term structure slope is measured as the spread between U.S. Treasury Constant Maturity three-month and ten-year rates as published by the U.S. Federal Reserve	Figlewski et al. (2008), Dang (2010)
Russell 2000 Index return (%)	The time series of Russell 2000 Index return were sourced from the website	Figlewski et al. (2008)
Political business cycle (time-varying)		
Dummy presidential election year	This dummy takes a value of one if the rating state commenced in a year when the presidential election took place (1984, 1988, 1992, 1996, 2000, 2004, 2008)	Beck (1987), Haynes et al. (1989, 1990, 1994), Klein (1996), Carlsen (1999), Pantzalis, Stangeland, and Turtle (2000)

Table 1 shows the variables employed in this study. Candidate variables were screened from previous studies on rating dynamics. Variables that exhibited strong multi-colliniarity were eliminated. Of 28 variables listed above, 3 time-independent variables capturing the current rating, 15 time-independent variables capture the rating history, 4 dummies capture the sub-sectors of FIs, and 6 time-varying variables capture macro-economic conditions and political business cycles. Time-independent variables were measured at the beginning of a rating state whereas time-varying variables were updated monthly during the survival duration of each rating state.

Table 2: Descriptive statistics of rating variables

Variables	Sample	Mean	Median	Std Dev	Minimum	Maximum	Skewness	Kurtosis
start_rating	Estimation	12.83	14 (BBB+)	4.21	1 (C)	21 (AAA)	-0.73	-0.31
	Holdout	13.04	14 (BBB+)	4.83	2 (CC)	21 (AAA)	-0.64	-0.55
dummy_inv_boundary	Estimation	0.26	0	0.44	0	1	1.12	-0.74
	Holdout	0.23	0	0.42	0	1	1.30	-0.31
dummy_junk_boundary	Estimation	0.13	0	0.33	0	1	2.23	2.99
	Holdout	0.11	0	0.32	0	1	2.46	4.06
age_since_first_rated (years)	Estimation	7.70	6.46	4.82	0.488	23.80	1.10	0.75
	Holdout	15.12	15.00	7.81	0.351	28.56	-0.11	-1.12
original_rating	Estimation	15.39	16 (A)	3.86	4 (CCC)	21 (AAA)	-0.53	-0.48
	Holdout	14.79	15 (A-)	3.66	5 (CCC+)	21 (AAA)	-0.36	-0.66
previous_rating1	Estimation	13.39	14 (BBB+)	3.90	2 (CC)	21 (AAA)	-0.58	-0.40
	Holdout	13.57	14 (BBB+)	4.16	2 (CC)	21 (AAA)	-0.60	-0.43
previous_rating2	Estimation	14.05	15 (A-)	3.74	2 (CC)	21 (AAA)	-0.49	-0.34
	Holdout	13.94	14 (BBB+)	3.69	2 (CC)	21 (AAA)	-0.58	-0.17
lag_one (years)	Estimation	1.92	1.36	1.97	0.00	14.43	2.44	8.74
	Holdout	2.69	1.24	3.69	0.00	23.47	2.51	7.27
lag_two (years)	Estimation	2.10	1.49	2.13	0.00	17.42	2.37	8.23
	Holdout	3.83	2.17	4.31	0.01	23.47	1.86	3.53
dummy_lag1_down	Estimation	0.67	1	0.47	0	1	-0.71	-1.50
	Holdout	0.63	1	0.48	0	1	-0.54	-1.72
dummy_lag2_down	Estimation	0.69	1	0.46	0	1	-0.82	-1.33
	Holdout	0.60	1	0.49	0	1	-0.42	-1.84
dummy_Fallen Angel	Estimation	0.26	0	0.44	0	1	1.10	-0.79
	Holdout	0.23	0	0.42	0	1	1.27	-0.40
dummy_Rising Star	Estimation	0.14	0	0.35	0	1	2.02	2.09
	Holdout	0.12	0	0.32	0	1	2.42	3.87
dummy_Not rated	Estimation	0.00	0	0.06	0	1	17.12	291.32
	Holdout	0.02	0	0.13	0	1	7.38	52.69
dummy_big_down	Estimation	0.14	0	0.35	0	1	2.10	2.43
	Holdout	0.16	0	0.37	0	1	1.88	1.56
dummy_big_up	Estimation	0.31	0	0.46	0	1	0.81	-1.34
	Holdout	0.25	0	0.43	0	1	1.16	-0.67
rate_prior_up	Estimation	0.18	0.15	0.22	0	1.87	3.26	18.44
	Holdout	0.14	0.12	0.13	0	0.85	1.82	6.07
rate_prior_down	Estimation	0.49	0.38	0.47	0	4.52	3.44	19.37
	Holdout	0.31	0.20	0.45	0	5.70	6.07	57.42

Table 2 reports the descriptive statistics of current rating and rating history variables for 884 observations in the estimation sample and 399 observations in the holdout sample.

Table 3: Descriptive statistics of survival time

Rating states	Sample	Number of observations	Mean (year)	Median (year)	Standard Deviation	Minimum (day)	Maximum (year)	Skewness	Kurtosis
Up states	Estimation	220	2.36	1.86	1.84	12	10.65	1.64	3.15
	Holdout	48	1.01	0.97	0.77	1	3.01	0.91	0.14
Down states	Estimation	407	1.32	0.69	1.69	1	13.11	3.45	17.47
	Holdout	223	0.73	0.38	0.89	1	3.87	1.77	2.36

Table 3 above presents the descriptive statistics of the survival times for down states and up states in the estimation and holdout period. Additional analysis (not reported) indicates that down states/ up states in the estimation and the holdout period have statistically different survival times.

Table 4: Proportional and dynamic Cox's hazard models for upgrades and downgrades, 1984-2004

Panel A: Parameter estimates

	Proportional models (with time-fixed covariates)						**Base models (with time varying covariates)**						**Extended models (with time-varying covariates)**					
	Upgrade model			**Downgrade model**			**Dynamic upgrade model**			**Dynamic downgrade model**			**Dynamic upgrade model**			**Dynamic downgrade model**		
Variables	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
Current rating																		
Start rating	-0.14039***	0.0193	0.869	-0.09736***	0.01376	0.907	NA			NA			-0.35331***	0.06822	0.702			
Dummy investment boundary	0.43004***	0.1411	1.537	-0.20078*	0.11371	0.818	NA			NA			0.44384***	0.15199	1.559	-0.24913**	0.1197	0.779
Dummy junk boundary							NA			NA			0.51367**	0.28285	1.671			
Rating history																		
Age since first rated	NA			NA														
Original rating	NA			NA			0.06504***	0.0217	1.067				0.11943***	0.02734	1.127			
Previous rating1	NA			NA			-0.16046***	0.0224	0.852	-0.11943***	0.0313	0.887	0.12*	0.07223	1.127	-0.11734***	0.0315	0.889
Previous rating2	NA			NA						0.07253**	0.0336	1.075				0.07347**	0.034	1.076
Lag one	NA			NA						-0.08038**	0.0366	0.923				-0.08481**	0.0364	0.919
Lag two	NA			NA			-0.12044**	0.0507	0.887				-0.10376**	0.04994	0.901			
Dummy lag1 down	NA			NA						1.35139***	0.1372	3.863	-0.79511***	0.25017	0.452	1.34759***	0.1365	3.848
Dummy lag2 down	NA			NA														
Dummy Fallen Angel	NA			NA									-0.69629**	0.27608	0.498			
Dummy Rising Star	NA			NA														
Dummy big down	NA			NA														
Dummy big up	NA			NA						0.43248***	0.1187	1.541	0.33415*	0.19059	1.397	0.42795***	0.1214	1.534
Dummy Not rated	NA			NA									1.80169***	0.29216	6.06			
Rate prior up	NA			NA														
Rate prior down	NA			NA														
Sector dummies																		
Dummy_Bank	NA			NA														
Dummy_Bank Holding Co.	NA			NA														
Dummy_Finance Co.	NA			NA														
Dummy_Saving and Loan Co.	NA			NA														

Panel A: Parameter estimates (cont.)

	Proportional models (with time-fixed covariates)						Base models (with time varying covariates)						Extended models (with time-varying covariates)					
	Upgrade model			Downgrade model			Dynamic upgrade model			Dynamic downgrade model			Dynamic upgrade model			Dynamic downgrade model		
Variables	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
Macro-economic(time-varying)																		
Dummy NBER recession	NA			NA						-0.5498**	0.217	0.577				-0.53425**	0.2151	0.586
Inflation (%)	NA			NA						1.68361**	0.7282	5.385				1.68425**	0.7221	5.388
Industrial production growth (%)	NA			NA			1.05146***	0.3126	2.862	-1.13881***	0.2621	0.32	1.12352***	0.32582	3.076	-1.13049***	0.2605	0.323
Term structure slope (%)	NA			NA			0.63279***	0.1234	1.883	-0.50823***	0.1181	0.602	0.65658***	0.12706	1.928	-0.50481***	0.1172	0.604
Russell 2000 Index return (%)	NA			NA			0.15639***	0.0583	1.169	-0.16187***	0.0461	0.851	0.16568***	0.05783	1.18	-0.1614***	0.0461	0.851
Political cycle (time-varying)																		
Dummy presidential election year	NA			NA			-0.2668*	0.1621	0.766				-0.28038*	0.1623	0.755			

Panel A reports the parameter, standard error, and hazard ratio of the significant variables in the downgrade/ upgrade proportional and dynamic Cox's hazard models estimated during the period 1984-2004. The proportional models include 3 time-independent variables capturing the current rating. The base dynamic models incorporate 25 variables, of which 15 time-independent variables capture the rating history, 4 dummies capture the sub-sectors of FIs, and 6 time-varying variables capture macro-economic conditions and political business cycles. The extended dynamic models extend the base dynamic models and include 3 time-independent variables present in the proportional models. In the interest of a parsimonious model, the backward stepwise estimation procedure is employed. Variables were retained in the models if they were significant at the 10 percent level or better according to the likelihood ratio test. Parameter estimates are given first followed by the corresponding p-value based on Wald chi-square tests. *** p-value ≤ 1%, ** 1%< p-value ≤ 5%, * 5%< p-value ≤ 10%. In interpreting Panel A, a negative coefficient reduces the hazard and therefore reduces the probability of the event being modeled. The reported hazard ratios represent the relative change in the hazard for a one unit change in the independent variable.

Panel B: Summary of the Number of Event and Censored Observations

	Proportional/ dynamic downgrade models					Proportional/ dynamic upgrade models				
	Total	Number of Event	Percent Event	Number of Censored	Percent Censored	Total	Number of Event	Percent Event	Number of Censored	Percent Censored
Estimation sample	884	407	46.04%	477	53.96%	884	220	24.89%	664	75.11%
Banks	200	77	38.50%	123	61.50%	200	58	29.00%	142	71.00%
Bank holding companies	313	154	49.20%	159	50.80%	313	73	23.32%	240	76.68%
Finance companies	156	79	50.64%	77	49.36%	156	37	23.72%	119	76.28%
Saving & loan companies	111	56	50.45%	55	49.55%	111	26	23.42%	85	76.58%
Other sub-sectors	104	41	39.42%	63	60.58%	104	26	25.00%	78	75.00%

Panel C: Model goodness of fit, 1984-2004

	Proportional models (with time-fixed covariates)		Base models (with time-varying covariates)		Extended models (with time-varying covariates)	
	Upgrade model	**Downgrade model**	**Dynamic upgrade model**	**Dynamic downgrade model**	**Dynamic upgrade model**	**Dynamic downgrade model**
-2 Log likelihood (without covariates)	2436.0	4827.4	2436.0	4827.4	2436.0	4827.4
-2 Log likelihood (with covariates)	2371.2	4761.1	2325.0	4551.9	2288.7	4547.3
Likelihood ratio Chi-square	64.9	66.3	111.1	275.5	147.3	280.0
Degree of freedom	2	2	7	10	14	11
Pr > ChiSq	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001

Panel B reports the number of rating states, the distribution of events and censored observations across sub-sectors in the estimation sample. Panel C reports the model fit statistics. The term *-2 Log-Likelihood* is the logarithm of the maximum likelihood estimator for the estimated model. The likelihood ratio is calculated as $LR=2(\ln L_1-\ln L_o)$ where L_1 is the log-likelihood of the estimated model and L_o is the log-likelihood of the model without covariates. Comparison of the log-likelihood statistics in Panel C shows that the explanatory power of each model is significantly improved as variables are added. The likelihood ratio reports that this improvement is significant at better than the 1 percent level.

Table 5: The AUROC curve for the survival estimates of holdout states

Forecast time	Proportional models		Base dynamic models		Extended dynamic models	
(year)	Upgrade	Downgrade	Upgrade	Downgrade	Upgrade	Downgrade
1	49.8	52.5	57.2	74.8	57.5	74.6
2	54.3	43.9	51.5	57.8	48.6	57.4

This table shows the area under the ROC (AUROC) curve of the one-year and two-year survival estimates for holdout rating states pooled over the period January 2005-March 2010. The AUROC measures the discrimination ability of the estimated model. Predictions made at random have an AUROC of 0.5. The higher the AUROC, the more accurate the model is in separating survived observations from migrated observations.

The proportional model explores the effect of the current rating on rating migration hazard. The base dynamic model examines the impact of issuer-heterogeneity (rating history, industry sub-sector) and time-heterogeneity (macro-economic climate and political business cycle) on rating dynamics. The extended dynamic model investigates the effect of all variables included in the proportional and the base dynamic model.