Predicting bank rating transitions using optimal competing risks survival analysis models☆

Philippe Louis[a,*], Elisabeth Van Laere[a,b,c], Bart Baesens[a,d]

[a] *Department of Decision Sciences and Information Management, Katholieke Universiteit Leuven Naamsestraat 69, 3000 Leuven, Belgium*
[b] *Risk Management Institute, National University of Singapore 21 Heng Mui Keng Terrace, Level 4, Singapore 119613*
[c] *Department Accounting & Finance, Vlerick Leuven Gent Management School, Reep 1, 9000 Ghent, Belgium*
[d] *School of Management, University of Southampton, SO17 1BJ Southampton, United Kingdom*

Abstract

In the aftermath of the financial crisis, this paper contributes to the literature by investigating which underlying determinants cause bank rating transitions. We put forward competing risks survival analysis models to explain credit transition hazards of financial institutions using macroeconomic factors and the rating history. We find that there exists a significant dependence of rating up- or downgrade transition hazards on rating specific covariates. It turns out that macro-economic covariates significantly explain the time to a rating downgrade. Our results confirm the momentum effect, meaning that a financial institution that has been recently up-/downgraded has a higher chance of being up-/downgraded again. To our knowledge, this is the first paper that attempts to build a survival analysis model that explains rating migrations for financial institutions.

Keywords: rating transitions, survival analysis, rating specific and macro-economic covariates, prediction accuracy

JEL: C14, C41, C51, C52, G15, G21

1. Introduction

Credit ratings provide a measure about the ability and willingness of an issuer to meet its financial obligations. They intend to be an instrument to compare credit risk across issuers, issues

☆Submitted to the Credit Scoring and Credit Control XII conference

*Corresponding author

Email addresses: Philippe.Louis@econ.kuleuven.be (Philippe Louis), evanlaere@nus.edu.sg (Elisabeth Van Laere), Bart.Baesens@econ.kuleuven.be (Bart Baesens)

and time. When assigning a credit rating, a rating agency takes into account issuer and issue-specific factors, macroeconomic and market factors, as well as regulatory and legal factors. Credit rating agencies (CRA) publish a substantial number of different ratings. A commonly used rating is the long-term issuer rating, which is a forward looking opinion about the creditworthiness of an obligor. This rating captures the credit rating agency's opinion of the issuer's relative level of credit risk and is expressed as a letter grade that ranges, for instance, from 'AAA' to 'D'. These ratings are of vital importance to an extensive group of stakeholders, such as investors and regulators.

Academic literature mainly focuses on corporate ratings, often excluding financial institutions from their sample. However, being able to thoroughly understand and measure changes in credit quality is of utmost importance for risk management and capital provisioning in financial institutions. Moreover, in the aftermath of the financial crisis, the ongoing debate on higher capital ratios, more stringent stress tests, etc., makes it vital to investigate which underlying determinants cause bank ratings changes without undue delay. As such, this article endeavors to make a significant contribution to the rather limited literature on bank rating transitions.

This paper is structured as follows. Section 2 provides the reader with an overview of the current literature. Section 3 describes the features of the dataset and the characteristics of the covariates that were included in the estimated model. The next section provides the reader with a concise overview of the applied semi-parametric survival analysis technique. Section 5 presents the estimation results and section 6 assesses the predictive power of the covariates. Finally, section 7 summarizes the results and concludes.

2. Literature

Credit rating migration modeling is an essential tool in credit risk analysis. A change in a rating indicates that the perceived credit quality of an issuer has either improved (i.e. rating upgrade) or deteriorated (i.e. rating downgrade). The earliest credit risk modeling literature focused more on the prediction and explanation of corporate bankruptcies (Beaver, 1966; Altman, 1968). Sinkey (1975) was one of the first academics to apply the discriminant analysis approach to identify the characteristics of problem banks. Subsequently, Martin (1977) introduced the use of logistic regression. He constructed an 'early warning model', which expressed the probability of future failure of financial institutions as a function of a group of variables obtained from the current period's balance sheet and income statement. Lane et al. (1986); Whalen (1991) applied the Cox proportional hazards model to predict bank failures. Eventually, besides default explanation and prediction modeling, research turned towards the explanation and prediction of rating migrations, which is essentially just a more fine-grained approach.

In rating migration models, the correct estimation of transition probabilities plays a crucial role. Often these probabilities are grouped in matrices. The most straightforward technique to build a rating transition matrix is the 'cohort method' that summarizes the evolution from 'start ratings' to 'end ratings' over a certain time horizon (e.g. 1 year). When out of N_j issuers, N_{jk} migrate from a certain rating j to a certain rating k, then the cohort methods states that the estimated transition probability for stochastically independent transitions is $\hat{p}_{jk} = (N_{jk}/N_j)$, where $k \neq j$. Consequently, the rating probabilities solely depend on the observed frequencies of rating changes during the arbitrary chosen time period.

For modeling purposes, transition matrices are often assumed to follow a first-order Markov process (Jarrow et al., 1997). This implies that only the current rating grade is relevant in determining future migration probabilities, hence ignoring historical information. In addition, migration probabilities are believed to be constant through time, known as the time-homogeneity assumption. A simple, time-homogeneous Markov model allows for the specification of the stochastic processes in terms of transition probabilities. Academic research has proven that the practical use of transition matrices that adhere to these assumptions is limited owing to several drawbacks. The Markov and time-homogeneity property only holds within a one- or two-year horizon (Jafry & Schuermann, 2004; Kiefer & Larson, 2007; Frydman & Schuermann, 2008). Furthermore, there is overwhelming academic evidence that the rating process is non-Markovian and not time-homogeneous in the long run. For example, Altman & Kao (1992); Kavvathas (2000); Lando & Skø deberg (2002); Hamilton & Cantor (2004); Christensen et al. (2004); Frydman & Schuermann (2008); Figlewski et al. (2012) report the existence of a momentum effect in ratings. Observations that recently migrated into a certain rating class have a higher probability of experiencing a further migration compared to other observations in the same rating class. Nickell et al. (2000) conclude that rating transition probabilities vary according to the state of the macro-economy, the obligor's domicile and industry.

Besides, the possibility of observing no transition from a certain j to a certain k during the time horizon may not true in other time periods. Moreover, the time stability of transition matrices is a major issue for credit risk estimation. It is not always plausible to assume that these probabilities remain stable in the future. In addition, valuable information such as the exact timing of a rating change and the length of time an issuer has had a certain rating is ignored.

In order to overcome these limitations, the academic community tried to explain rating changes using a set of independent variables. For example, in the past researchers included factors that are related to the company itself and to the environment in which it is operating. For example, Nickell et al. (2000) fit an ordered probit model and conclude that rating transition probabilities vary according to the state of the macro-economy. Using survival analysis, Kavvathas (2000) reaches the same conclusion. Bangia et al. (2002) divide the economy into two regimes, expansion and contraction, and condition the migration matrix on these states. They find that ratings migration probabilities vary with the business cycle. Frydman & Schuermann (2008) employ Markov mixture models, estimating two economic regimes and find that rating are not time-homogeneous after controlling for the state of the macro-economy. Figlewski et al. (2012) analyze macro-economic and rating history related factors by applying survival analysis and decide that these factors are significant in explaining rating transitions.

Table 1 gives an overview of the literature on rating transitions. The author(s) and title can be found in the first column. The second column lists the used technique, and the third column lists the included variables in the model. Finally, the evaluation methodology is described in the last column.

3. Data

3.1. Credit rating data

This section describes some basic aspects of the rating transition data we obtained from the S&P RatingXpress database. The database contains information on the timing of credit rating migrations of 982 US financial institutions from February 1953 to August 2009. We confined our sample period to January 1994–December 2008 to make sure that all the covariate information, described in subsection 3.2, was available. While the original data has a wide range of long term rating symbols, we only kept the main rating symbols (AAA, AA, A, BBB, BB, B, CCC, CC, C, D). Rating modifiers + and − were omitted and only issuer credit ratings were retained. Two distinct kinds of events (also known as failures) can occur mutually exclusively at a certain time.

Paper	Technique	Explanatory variables	Evaluation
Nickell et al. (2000) – Stability of rating transitions	Ordered probit model	Real GDP growth, issuer industry and domicile	t-statistics
Hu et al. (2002) – The estimation of transition matrices for sovereign credit ratings	Ordered probit model, Bayesian approach to combine S&P's estimate and OPM estimate of transition matrix	Previous year default dummy, debt to GNP ratio, foreign exchange reserves to total imports ratio, inflation, industrial country dummy	R^2, percentage correctly classified
Bangia et al. (2002) – Ratings migration and the business cycle, with application to credit portfolio stress testing	Regime switching approach	Expanding or contracting economy indicator (NBER)	No evaluation
Hamilton & Cantor (2004) – Rating Transition and Default Rates Conditioned on Outlooks	Cohort approach	Past rating changes, current rating outlooks	No evaluation
Jafry & Schuermann (2004) – Measurement, estimation and comparison of credit migration matrices	Cohort and time homogeneous and non-homogeneous survival approach	Economic recession or expansion indicator	Average singular value of the mobility matrix
Trück (2008) – Forecasting credit migration matrices with business cycle effects - a model comparison	Comparison of factor model approach and numerical adjustment methods	Unemployment rate, GDP growth, CPI change, annual savings, consumption expenditure, T-bond spread	D_1 an D_2 risk sensitive difference indices, L_1 and L_2 norms
Figlewski et al. (2012) – Modeling the Effect of Macroeconomic Factors on Corporate Default and Credit Rating Transitions	Survival analysis	Initial and current rating class, recent up- and downgrades, years since first rated, unemployment rate, inflation, NBER recession indicator, CFNAI, real GDP growth, industrial production change, 3-month T-bill rate, 10-year Treasury bond yield, S&P 500 return, S&P 500 volatility, Russell 2000 return, yield spread Baa corporates and constant 10-year Treasuries, overall corporate bonds' default rate	Backward selection, z-statistic

Table 1: Overview of rating migration literature

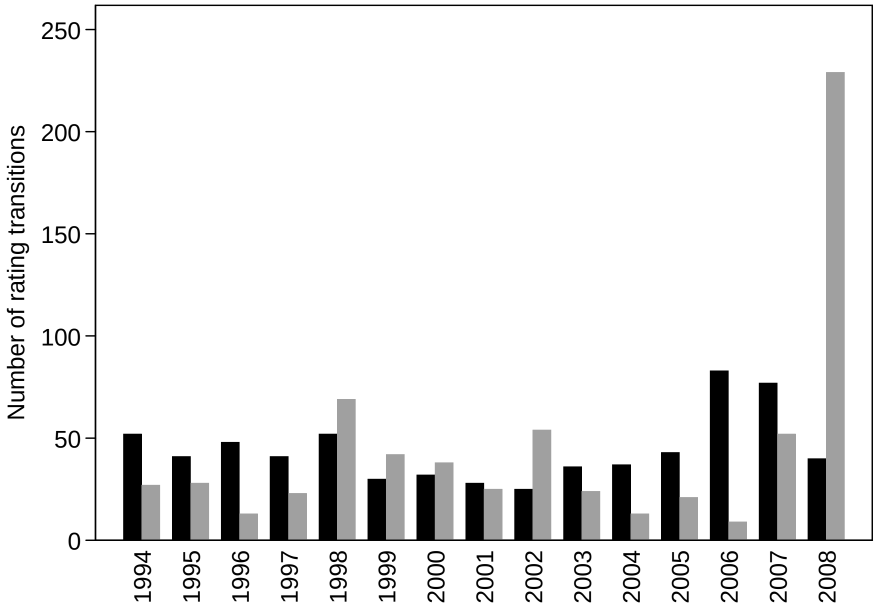

Figure 1: Number of annual rating transitions. Black bars indicate the number of rating upgrades whereas gray bars calculate the number of downgrades.

On the one hand, a financial institution's credit rating can be upgraded. On the other hand, a credit rating downgrade is possible. For every year, the number of rating transitions is depicted in figure 1. Our sample includes three contraction periods (1998, 2002, and 2008). As expected, the number of rating downgrades shot up dramatically in 2008 due to the financial crisis.

The sample consists of 755 unique banks and 3,731 spells of duration t. When a bank experienced multiple similar events (e.g. two downgrades) during the same month, the events were treated as a single event in the analysis. Eventually, 643 rating upgrades and 603 rating downgrades were observed. The median time to a rating change was 66 months (Std. Err.: 2.814) for upgrades and 81 months (Std. Err.: 5.709) for downgrades.[1]

[1]The median times to a rating change are calculated from $\hat{S}(t)$, the product limit estimate (also known as the Kaplan-Meier estimate) of the survivor function (see formula 1 on page 11). The large-sample standard error is estimated as $\frac{\hat{V}(\hat{S}(t_{50}))}{\hat{f}(t_{50})^2}$, where $\hat{f}(t_{50})$ is the estimated density function at the median. (Klein & Moeschberger, 2003)

Name	Model variable	Mean	SD	Median
Current rating class	Categorical (9=AAA,...,1=D)	6.818	1.057	7 (A)
Outlook	Categorical (2=Pos.,1=Stable,0=Neg.)	.978	.482	1 (Stable)
# of rating Δ past 24m	Continuous	.286	.567	0

Table 2: Description of the rating specific covariates

3.2. Covariates

3.2.1. Rating specific covariates

Data on three rating specific variables were collected. Table 2 provides some summary statistics on these covariates.

- Current rating symbol: Obviously, the financial institution's current rating is the most important signal of its credit quality. A dummy variable was formed for each category. The base level was chosen to be BBB.
- Outlook: An outlook is a forward looking opinion about potential changes in the current rating symbol. As such, it provides a key indication of the future creditworthiness of an issuer. Dummies were created for each of the three categorical levels (positive, stable, and negative). Stable was set to be the base level.
- Number of rating changes in the past 24 months: To determine the effect of serial correlation, we created a variable that counts the number of rating migrations in the past 24 months. The variable ranges from 0 to 7.

3.2.2. Macro-economic covariates

It goes without saying that the conditions of the macroeconomy will influence the hazard of a rating up- or downgrade. Therefore variables were included in the model to control for the state of the economy prior to or at each rating event. Covariate time series were downloaded for every month between January 1994–December 2008. We have selected 18 macroeconomic covariates. These covariates fall into three main categories: current state of the macro-economy, future direction of the macro-economy, and current financial markets condition. When no monthly data was available, monthly estimates were calculated from the different sampling frequencies (e.g. quarterly) by fitting a cubic spline curve which is constrained to pass through the given

Name	Source	Mean	SD	Median	Skewness	Kurtosis	Upgr. / downgr.
Output gap (% of pot. GDP at AR)	IMF	-.050	1.304	-.104	-.290	3.817	+/−
Inflation (CPI-U) (% at SAAR)	BLS	2.658	3.650	2.509	-.622	7.715	
Unemployment rate (% at AR)	BLS	5.098	.692	5.136	.112	2.234	−/+
Capacity utilization rate (% at AR)	FED	80.61	3.199	81.25	-.650	2.271	+/−
Gross national savings (% of GDP at AR)	IMF	16.16	1.891	16.19	-.375	2.332	+/−
Curr. account balance (% of GDP at AR)	IMF	-3.65	1.531	-3.96	.081	1.642	
Government gross debt (% of GDP at AR)	IMF	63.53	5.927	61.65	.379	2.554	
Real GDP growth (% at SAR)	BEA	2.954	2.498	2.991	-.720	5.382	+/−
Bankruptcy filings (Δ% at AR)	USC	-.747	17.262	-4.564	1.117	5.610	−/+
New orders change (Δ% at AR)	CB	4.230	5.722	5.230	-1.649	8.633	+/−
New cars change (Δ% at AR)	CB	11.96	22.02	11.28	.282	2.285	+/−
New housing change (Δ% at AR)	CB	.333	13.63	4.347	-1.191	4.497	+/−
T-bill rate 3m	DS	3.909	1.687	4.672	-.679	2.007	
Treasury yield adj. to const. maturity 20y	DS	5.840	.9518	5.755	.357	2.269	
Prime rate (month avg.)	DS	7.175	1.712	8.030	-.702	1.998	
Interbank rate 3m (month avg.)	DS	4.449	1.720	5.346	-.744	2.099	−/+
KBW bank index return	DS	.7769	5.559	.9977	-.688	5.561	+/−
S&P500 return	DS	.6426	3.865	1.092	-.830	4.468	+/−

Table 3: Univariate statistics on the included macro-economic covariates. AR = Annual rate, SAAR = Seasonally adjusted annual rates; IMF = International monetary fund, BLS = Bureau of Labor Statistics, FED = Federal Reserve, BEA = Bureau of Economic Analysis, USC = US Courts, CB = Census Bureau, DS = Datastream

datapoints. Since the influence of the covariates on the rating transition hazard is not expected to be instantaneous, it was deemed necessary to include lagged effects. However, we did not want to specify a model with too many covariates. Consequently, the time series data was exponentially filtered with smoothing parameter α. This parameter determines how quickly the smoothed series will adjust to changes in the original series. We have set it equal to .9 for the current state of the macro-economy and financial markets covariates, and equal to .2 for the future direction of the macro-economy covariates. Hence, more emphasis is placed on the most recent observations of the first group, whereas the response to changes in the second group is slower to reduce the impact of temporary shocks.

Table 3 gives the reader an overview of some univariate statistics on the included covariates.

- Output gap as a percentage of the potential GDP at annual rates: Calculated as the actual GDP less the potential GDP as a percent of the potential GDP at annual rates. A positive number says that the growth of aggregate demand is stronger than the growth of aggregate supply; a negative number indicates the opposite. We expect its coefficient to be positive for upgrade migrations and negative for downgrade migrations.

- Inflation –CPI for All Urban Consumers (CPI-U)– in percentage at seasonally adjusted annual rates: To capture the changes in the price level of goods and services, we use the seasonally adjusted historical all urban consumer price index. Inflation's effects are expected to be double-edged. Uncertainty over future inflation may discourage investment and savings. Furthermore, financial institutions are sensitive to large swings in the inflation rate as banks typically deal with nominal financial instruments with a fixed value. For instance, when a bank grants a loan, the repayments are fixed at nominal value. As such, inflation reduces the real value of the required debt repayments. As a result, traditional financial institutions that convert shorter-term deposits to longer-term loans, mortgages, etc. can be badly affected by spikes in inflation. However, when a bank has to service its own debt, inflation reduces its real value. Consequently, we cannot determine the expected effect of inflation.

- Unemployment percentage at annual rates: The unemployment rate calculates the number of unemployed as a percent of the labor force. It provides a good indicator of the overall health of the economy. A high unemployment rate is expected to influence rating upgrades negatively and rating downgrades positively.

- Capacity utilization rate: The capacity utilization rate is the ratio of the output that is actually produced to the potential output that theoretically could be produced if capacity was fully used. Usually, an increase in this percentage signals a possible market demand growth, while a decrease signals an economic slowdown. Hence, its coefficient is anticipated to be positive for upgrade migrations and negative for downgrade migrations.

- Gross national savings as a percentage of GDP at annual rates: Gross national savings are calculated as the gross disposable income less final consumption expenditure. Gross national savings include transactions from all sectors or economic agents. A high rate usually indicates a country's high potential to invest. As such, a high rate is expected to influence rating upgrades positively and rating downgrades negatively.

- Current account balance as a percentage of GDP at annual rates and government gross debt as a percentage of GDP at annual rates: The current account balance is a significant measure of a country's foreign trade affairs. A surplus implies that the country is a capital exporter whereas a deficit implies the reverse. Financial institutions typically hold a lot of government debt. Consequently, if the US government's burden of debt increases, its creditworthiness will decrease, conceivably affecting the banks as well. However, the gross debt to GDP ratio has varied a lot in the past with relatively little effect on general economic growth. As such, while an increase could influence upgrades negatively and downgrades positively, the exact effect can not be predicted.

- Treasury bill rate 3 months and 20 years treasury yield at constant maturity: The impact of a high yield on the hazard of rating transitions is ambiguous. In general, smaller, traditional financial institutions are more asset sensitive, earning more money when interest rates are high. In contrast, larger banks are often more liability sensitive because they depend more on interest rate sensitive funding. Therefore, they could be negatively affected when interest rates are high. More generally, the treasury yields affect the entire economy. For example, a high interest rate makes it more expensive to buy a house, harmfully impacting the new housing change covariate. This in turn has a negative impact on the economy and results in a slowdown of the economy. In sum, although the coefficients on either treasury product could be thought to be negative in upgrade migrations and positive in downgrade migrations, the precise impact can not be assessed.

- Prime rate: The prime lending rate is a reference interest rate used by banks. The effect of a high prime rate could be twofold. On the one hand, it can act as a signal to indicate economic tightness. One the other hand, financial institutions will earn more when the prime rate is high. As such, the expected coefficients are not clear.

- Interbank rate: The interbank rate is the interest rate banks charge for short-term loans between them and other banks. Most loans are for very short maturities (i.e. one week or less). Interbank loans are extremely important to the banking system as they allow financial institutions to cover temporary liquidity shortfalls. As such, a surge in the interbank rate can suggest a loss of confidence. Therefore, a high interbank rate is expected to influence upgrades negatively and downgrades positively.

- KBW bank index and S&P500 return: The monthly returns of the stock market serve as an indicator of the overall health of the banking and corporate sector. Thus, we expect the coefficients to be positive for upgrade migrations and negative for downgrade migrations.

4. Methodology

As discussed in section 2, various approaches to model the relationship between the outcome variable (i.e. a rating transition) and a group of covariates exist. In this paper we will use a competing risk survival analysis model. Survival analysis treats, in contrast to other methods, the time to the occurrence of the event of interest as the outcome variable. Furthermore, survival analysis deals well with censoring. A censored observation is one whose exact event time is unknown. This could happen when the issuer's rating class does not change during the observation period or when the rating is withdrawn. Suppose T is a non-negative random variable that measures the amount of time an issuer spends in a certain rating class. T's survival function, $S(t)$, gives the probability that an issuer does not experience a rating transition beyond a certain time t:

$$S(t) = \Pr(T > t) \qquad 0 < t < \infty \tag{1}$$

Obviously, $S(t)$ is a decreasing right-continuous function of t with $S(0) = 1$ and $\lim_{t\to\infty} S(t) = 0$ (Kalbfleisch & Prentice, 2002).

The most widely used survival analysis approach to link the outcome and predictor variables is the Cox hazard regression model (Cox, 1972). This paper uses an extended version of the Cox model that allows for time-varying covariates. Suppose we build a vector that is expected to be predictive of rating migrations for each subject still under investigation at every time horizon. More specifically, given that we have p covariates, at a certain time t the covariates vector $\mathbf{x}$ is equal to (Hosmer et al., 2008):

$$\mathbf{x}'(t) = [x_1(t), x_2(t), \ldots, x_p(t)] \tag{2}$$

where $t < T$.

Closely related to the survival function is the hazard function. It calculates the instantaneous rate of a rating event i (e.g. a rating upgrade) in a certain time interval, given that the issuer has survived up to t.

$$h_i(t, \mathbf{x}(t)) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T < t + \Delta t, I = i | T \geq t, \mathbf{x}(t))}{\Delta t} \tag{3}$$

The Cox hazard model specifies $h_i(t, \mathbf{x}(t))$ to be of the form:

$$h_i(t, \mathbf{x}(t)) = h_{0i}(t) \exp[\mathbf{x}'(t)\beta_i] \tag{4}$$

where $i \in I$ and β_i is a vector of regression coefficients. The hazard function is the product of two distinct parts. The non-parametric baseline function $h_0(t)$ captures how the hazard function changes as a function of time. The second part determines how the hazard changes as a function of the issuer covariates which are affected by time.

One of the most appealing properties of the Cox model is the possibility to estimate the β's without having to specify the baseline part. The model parameter β's are derived by maximizing a partial likelihood function L. The function only incorporates probabilities for the issuers that are subject to the rating event i, ignoring probabilities for the censored issuers. It can be understood as the product of the likelihood function for the each of the K event times: $\prod_{k=1}^{K} L_k = L_1 \times L_2 \times \ldots \times L_K$. Since tied values among the uncensored survival times are present, we make use of the Efron (1977) approximation. Suppose that the sample contains k uncensored failure times and that d_j issuers undergo a rating event at time t_j where $j = 1, 2, \ldots, T$. Then x_j is equal to the sum of the covariates over the d_j issuers. The partial likelihood for β using the Efron approximation is then equal to:

$$L(\beta) = \prod_{j=1}^{K} \frac{\exp[\mathbf{x}_j(t_j)'\beta]}{\prod_{r=1}^{d_j}(\sum_{l \in R(t_j)} \exp[\mathbf{x}_l(t_l)'\beta] - \frac{r-1}{d_j} \sum_{l \in D(t_j)} \exp[\mathbf{x}_l(t_l)'\beta])} \tag{5}$$

In the time-varying Cox model, the lagged values of the covariates are updated monthly, and the model incorporates these values prior to or at each event time.

Multiple events may occur to the same financial institution when it is subjected to several rating up- or downgrades. As a result, event times could be correlated within a cluster (i.e. a distinct bank). The traditional survival analysis requirement that failure times are independent will thus be violated. Therefore, we cluster across distinct financial institutions specifies that the standard errors allow for intra-cluster event time correlation, keeping the latter independent across clusters but not necessarily within.

5. Results

Tables 4 and 5 report the estimated hazard ratios and robust standard errors for several model specifications. For both rating events, four models were estimated: a full model including all covariates; a backward stepwise model, where .05 was the significance level; a rating specific factors only model; and a macro factors only model.

When interpreting the results recall that the hazard rate, which calculates the instantaneous likelihood per unit of time for the event to occur, is equal to exp(coefficient). As such, a negative coefficient reduces the hazard rate (i.e. $HR < 1$) and a positive coefficient increases the hazard rate (i.e. $HR > 1$).

5.1. Effects of rating specific covariates

As could be expected, there is a significant dependence of the rating up- and downgrade transition hazards on rating specific covariates. The current rating, which was expected to be an important signal of credit quality, affects up- and downgrades differently. The hazard rate of a rating upgrade is significantly lower for all but one rating symbol compared to the base symbol BBB. In contrast, only the highly speculative issuers have a statistically different downgrade hazard rate. Furthermore, their hazard is much lower than 1, indicating that they are substantially less likely to be downgraded. This could indicate that S&P is wary to further downgrade financial institutions that are already deemed to be highly speculative. Both for rating up- and downgrades, positive and negative outlooks act as very significant indicators for future rating changes. In agreement with earlier research, we confirm a highly significant rating momentum effect. Financial institutions that migrated in the past 24 months have a higher chance of experiencing another rating transition. This refutes the Markov assumption, as mentioned in section 2.

An important result is that estimated hazard ratios differ very little between the full model and the rating specific model. This signals that the rating specific covariates and the macro-economic covariates truly capture different information and as such both groups of covariates should be included in a well specified model.

5.2. Effects of macro-economic covariates

We start by considering the influence of each of the macro-economic covariates. However, when comparing the effects of the different covariates, we must be aware that the hazard ratios were estimated on the covariates using their natural scale. The hazard ratio reports the effect of increasing the value of the covariate by 1. Since the scale of the covariates varies, it is not possible to directly determine the impact of the macro-economic covariates. However, significant covariates and their respective coefficients will give us an idea of their potential importance and of the direction of their effect.

In the comprehensive rating upgrade model, only 3 macro-economic covariates are significant, whereas 9 macro-economic covariates are significant in the full rating downgrade model. This clearly indicates that credit rating downgrade decisions are genuinely influenced by the state of the macro-economy.

5.2.1. Rating upgrade model

The three months T-bill rate is the only macro-economic covariate that performs well in every model specification. It is highly significant and its positive coefficient indicates a high rate increases the hazard of a rating upgrade. In the interest of finding a more parsimonious model, we performed a backward stepwise regression. One current state of the macro-economy and one current financial markets condition covariate turn out to be significant. The gross national savings coefficient has the right sign. More savings as a percentage of GDP thus seem to positively impact the hazard ratio for rating upgrades. This result is consistent with our a priori expectation. Furthermore, it turns out that the gross national savings rate is also a significant covariate in a rating downgrade model.

5.2.2. Rating downgrade model

A backward stepwise procedure reduced the number of covariates until all remaining seven coefficients were significant at the 5% level or better. Six of these covariates are significant in every model specification. Instead of the three months T-bill rate, the treasury yield and prime rate are now significant. The negative coefficients imply that a high rate reduces the hazard of a rating downgrade. The importance of the interbank rate as an covariate cannot be understated. As expected, a high interbank rate signals a malign situation, dramatically increasing the hazard ratio.

The government gross debt as a percentage of GDP coefficient clearly points out that an increase in US government debt has a negative impact on the creditworthiness of their domestic banks. However, we believe that these results may be biased by the financial crisis. Therefore, we reestimate the backward stepwise model for rating downgrades after dropping all events in 2008. It turns out that the current account covariate is no longer significant. The government gross debt hazard ratio is then equal to 1.595*** (SE: .1132).

	Full model	Stepwise model	Rating specific model	Macro factors model
Current rating symbol: base level BBB				
CC and C	.0221***	.0226***	.0373***	
	(.0224)	(.0208)	(.0319)	
CCC	.0040***	.0033***	.0039***	
	(.0058)	(0046)	(.0055)	
B	.4412*	.4527***	.4474***	
	(.1469)	(.1453)	(.1370)	
BB	1.258	1.270	1.115	
	(.3343)	(.3346)	(.3050)	
A	.5941***	.5863***	.5548***	
	(.0816)	(.0803)	(.0749)	
AA	.5524**	.5517***	.4751***	
	(.1014)	(.1027)	(.0815)	
Outlook: base level Stable				
Negative	.1033***	.0951***	.1135***	
	(.0512)	(.0447)	(.0477)	
Positive	6.4228***	6.4885***	6.603***	
	(.8206)	(.8139)	(.9076)	
# rating Δ past 24m	12.924***	12.957***	10.396***	
	(1.611)	(1.579)	(1.3625)	
Output gap	.4210**			.9118
	(.1278)			(.1451)
Inflation	.9724*			.9878
	(.0137)			(.0122)
Unemployment rate	.6624			.6539
	(.2894)			(.1779)
Capacity utilization rate	1.122			.8535
	(.1757)			(.0825)
Gross national savings	1.3581	1.286**		.9172
	(.3229)	(.1248)		(.0981)
Curr. account balance	.8416			1.014
	(.1565)			(.1289)
Government gross debt	1.0315			1.115**
	(.0578)			(.0422)
Real GDP growth	1.0577			1.117***
	(.0357)			(.0309)
Bankruptcy filings	.9966			.9989
	(.0058)			(.0039)
New orders change	.9897			1.015
	(.0357)			(.0235)
New cars change	.9999			.9980
	(.0027)			(.0021)
New housing change	1.001			.9947
	(.0083)			(.0064)
T-bill rate 3m	3.166***	3.421***		3.049***
	(1.032)	(.6694)		(.6262)
Treasury yield	1.123			.6525*
	(.2689)			(.1137)
Prime rate	.5494			.7723
	(.2302)			(.2274)
Interbank rate 3m	.6375			.6245
	(.2967)			(.2024)
KBW bank index return	1.006			1.026*
	(.0147)			(.0116)
S&P500 return	.9871			.9573*
	(.0209)			(.0176)

Table 4: Survival analysis estimation results for rating upgrades. First row number reports the hazard ratio, second row number is the robust standard error. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	Full model	Stepwise model	Rating specific model	Macro factors model
Current rating symbol: base level BBB				
CC and C	.0018***	.0018***	.0029***	
	(.0023)	(.0022)	(.0036)	
CCC	.2346*	.2192**	.1006**	
	(.1537)	(.1469)	(.0766)	
B	.5360	.5515	.3819**	
	(.1766)	(.1818)	(.1370)	
BB	1.548	1.547	1.221	
	(.3564)	(.3591)	(.2634)	
A	.9384	.9540	1.011	
	(.1284)	(.1310)	(.1405)	
AA	.8734	.8982	1.095	
	(.1321)	(.1357)	(.1673)	
AAA	1.021	1.034	1.064	
	(.2486)	(.2507)	(.2848)	
Outlook: base level Stable				
Negative	5.3642***	5.379***	5.816***	
	(.6381)	(.6415)	(.6700)	
Positive	.1924***	.1928***	.1968***	
	(.0872)	(.0876)	(.0899)	
# rating Δ past 24m	5.698***	5.660***	5.915***	
	(.5228)	(.5155)	(.5019)	
Output gap	1.025			.7782
	(.2538)			(.1390)
Inflation	1.009			.9895
	(.0177)			(.0142)
Unemployment rate	1.276			.5443*
	(.4673)			(.1513)
Capacity utilization rate	1.342*			1.133
	(.1915)			(.1157)
Gross national savings	.5300**	.4918***		.7848
	(.1266)	(.0647)		(.1078)
Curr. account balance	.8011***	.7977***		.8406***
	(.0479)	(.0385)		(.0403)
Government gross debt	3.062***	3.040***		2.778***
	(.7783)	(.6855)		(.5394)
Real GDP growth	.9723			.9684
	(.0274)			(.0261)
Bankruptcy filings	.9935			1.000
	.0068			(.0055)
New orders change	1.025			1.042
	(.0302)			(.0226)
New cars change	.9997			1.000
	(.0033)			(.0028)
New housing change	1.017*			1.005
	.0085			(.0078)
T-bill rate 3m	.7632			.6205*
	(.1833)			(.1315)
Treasury yield	.5427**	.5621**		.3820***
	(.1261)	(.1108)		(.0707)
Prime rate	.1087***	.0953***		.0778***
	(.0456)	(.0335)		(.0261)
Interbank rate 3m	11.24***	9.194***		15.849***
	(5.07)	(3.10)		(5.781)
KBW bank index return	.9641**	.9664***		.9659***
	(.0109)	(.0074)		(.0099)
S&P500 return	.9989			.9917
	(.0179)			(.0150)

Table 5: Survival analysis estimation results for rating downgrades. First row number reports the hazard ratio, second row number is the robust standard error. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6. Validation and predictive power

The survival analysis Cox model is often used to forecast events where the outcome is the time to an event, and specifically in this paper the outcome is the time until a credit rating is either up- or downgraded. It is vital to quantify how the outcome is determined through the covariates and regression coefficients. A major drawback of including time-varying covariates in a survival analysis is that measures that determine whether predictions and outcomes are concordant (e.g. Harrell's C) are unsuitable.[2]

Eventually, we used three approaches to validate our results and to assess the potential predictive power of the covariates.

Firstly, using bootstrap sampling with replacement, a backward stepwise survival analysis estimation was run 500 times for each of the two events. The significance level for removal from the model was et equal to .15; and the level for addition to the model was set to .05. The first column of table 6 reports the number of times a covariate was included in the final backward stepwise model.

Secondly, we performed a Wald test to evaluate the difference between a model without covariates and a model in which every covariate is separately included, under the null hypothesis that the covariate is equal to zero. If we fail to reject the null hypothesis, the covariate is not significantly helpful in predicting the time to the occurrence of the event of interest. The Wald test result can be found in the second column.

Thirdly, Kent & O'Quigley (1988) developed a measure of dependence as a reduction in entropy through the Kullback & Leibler (1951) distance between the semiparametric Cox model and the parametric Weibull model. As such, their measure captures the proportion of the explained randomness of the model.

For the Cox model, O'Quigley et al. (2005) proposed a new statistic

$$\rho_a^2 = 1 - \exp\left(-\frac{Z^2}{e}\right) \tag{6}$$

where e is the number of events, Z^2 denotes the likelihood ratio statistic to compare the fitted

[2]A desirable measure of discrimination has several qualities: (a) relatively unaffected by the amount of censoring; (b) ρ^2 increases with the degree of association; (c) for two nested models $M_1 \subset M_2$, $\rho^2(M_1) < \rho^2(M_2)$; (d) confidence intervals can be calculated (Royston & Sauerbrei, 2004).

model with the null model. This statistic has the nesting property but slightly fails the censoring property (upward bias when censoring is more prevalent (O'Quigley et al., 2005, tables I and II)).

Royston (2006) proposes an improved version of equation (6) as

$$\rho^2 = \frac{\rho_a^2}{\rho_a^2 + (\pi^2/6)(1 - \rho_a^2)} \tag{7}$$

that has all the desirable qualities of a good measure of discrimination.

Since the standard errors of our model are corrected for clustering effects, the standard likelihood ratio test is no longer valid. Therefore instead of using the likelihood ratio statistic in equation (6), we use the Wald test statistic. Furthermore, the equation (6) was originally proposed for Cox proportional hazard models. Because our model does not adhere to this assumption, the resulting ρ^2 is not interpretable as a measure of explained variation but only as a measure of explained randomness. We report the statistic in the third column.

Table 6 shows that the rating specific covariates are vital in explaining the time to a rating event. All these covariates were included in every backward stepwise model. Remarkably, the macro-economic covariates influence in the rating upgrade model is limited. In contrast, including a wide range of macro-economic covariates in a rating downgrade model will significantly improve its explanatory power.

7. Conclusion and future research

To our knowledge, this is the first paper to investigate the effect of both rating specific and macro-economic covariates on financial institutions' rating migrations using a semi-parametric survival analysis framework, which treats the time to to occurrence of an event of interest (i.e. a rating up- or downgrade) as the outcome variable.

We found that there exists a significant dependence of rating up- or downgrade transition hazards on rating specific covariates. Highly speculative banks have a lower hazard rates, which could perhaps indicate that S&P does not easily further downgrades a bank with low creditworthiness. Next, outlooks act as a very significant signal for future rating changes. Our results confirm the momentum effect, meaning that a financial institution that has been recently up-/downgraded has a higher chance of being up-/downgraded again. An important result is that the estimated rating specific hazard ratios vary very little between a model in which macro-economic covariates are

Name	Rating upgrade (1)	Rating upgrade (2)	Rating upgrade (3)	Rating downgrade (1)	Rating downgrade (2)	Rating downgrade (3)
Current rating class: base level BBB	500	78.40	.0961	500	153.57	.0196
	(0)	(.0000)	(.0082)	(0)	(.0000)	(.0162)
Outlook: base level Stable	500	649.98	.4146	500	811.37	.7164
	(0)	(.0000)	.0390	(0)	(.0000)	(.0269)
# rating Δ past 24m	500	293.56	.8151	500	261.47	.8863
	(0)	(.0000)	(.0199)	(0)	(.0000)	(.0152)
Output gap	82	1.77	.0015	36	176.57	.3349
	(8.288)	(.1830)	(.0015)	(5.786)	(.0000)	(.0481)
Inflation	405	.33	.0003	81	133.09	.1626
	(8.781)	(.5632)	(.0031)	(8.247)	(.0000)	(.0346)
Unemployment rate	380	.02	.0000	83	31.49	.0912
	(9.559)	(.8833)	(.0010)	(8.328)	(.0000)	(.0305)
Capacity utilization rate	391	3.79	.0031	450	125.84	.1658
	(9.242)	(.0517)	(.0026)	(6.715)	(.0000)	(.0250)
Gross national savings	469	9.63	.0082	493	120.75	.2947
	(5.398)	(.0019)	(.0045)	(2.630)	(.0000)	(.0417)
Curr. account balance	82	7.69	.0101	500	11.35	.0117
	(8.288)	(.0055)	.0060	(0)	(.0000)	(.0034)
Government gross debt	155	13.62	.0116	500	67.47	.2075
	(10.352)	(.0002)	(.0046)	(0)	(.0000)	(.0561)
Real GDP growth	398	.24	.0002	149	334.89	.3669
	(9.020)	(.6260)	(.0010)	(10.24)	(.0000)	(.0499)
Bankruptcy filings	94	1.87	.0020	64	308.42	.3864
	(8.745)	(.1716)	(.0022)	7.478	(.0000)	(.0421)
New orders change	207	12.11	.0161	86	467.41	.3332
	(11.02)	(.0005)	(.0079)	(8.447)	(.0000)	(.0445)
New cars change	72	.00	.0000	69	88.81	.1524
	(7.858)	(.9782)	(.0027)	(7.720)	(.0000)	(.0155)
New housing change	160	24.02	.0204	306	259.94	.3631
	(10.44)	(.0000)	(.0064)	10.91	(.0000)	(.0332)
T-bill rate 3m	500	3.88	.0031	126	126.93	.2117
	(0)	(.0488)	(.0047)	(9.718)	(.0000)	(.0393)
Treasury yield	98	11.06	.0128	488	99.54	.2374
	(8.886)	(.0009)	(0057)	(3.426)	(.0000)	(.0233)
Prime rate	85	2.22	.0017	500	84.84	.1205
	(8.408)	(.1365)	(.0024)	(0)	(.0000)	(.0250)
Interbank rate 3m	429	3.39	.0027	500	45.16	.0525
	(7.813)	(.0657)	(.0032)	(0)	(.0000)	(.0118)
KBW bank index return	121	.46	.0003	488	247.07	.2257
	(9.587)	(.4969)	(.0010)	(3.426)	(.0000)	(.0308)
S&P500 return	326	.50	.0004	49	291.69	.2878
	(10.66)	(.4786)	(.0012)	(6.655)	(.0000)	(.0303)

Table 6: Validation results. The first column reports the bootstrap with replacment results (first row: #, second row: standard error), the second column reports the Wald test (first row: $\chi(1)$ statistic, second row: p-value), the third column reports the measure of discrimination statistic (first row: statistic, second row: bootstrapped standard error).

included and one in which they are omitted. Consequently, the rating specific and macro-economic covariates truly capture different information and the information contained in the macro-economic covariates is incremental to that in the rating specific covariates. However, the influence of the macro-economic covariates differs between the events. It turns out that the macro-economic covariates explain the time to a rating upgrade to a lesser extent than the time to a rating downgrade. The effect of interest rates on financial institutions is twofold. On the one hand, banks potential for rating upgrades increases when interest rates are high (e.g. three months T-bill). On the other hand, when the interbank rate rises, financial institutions appear to be negatively impacted as the interbank rate coefficient is significantly positive in the downgrade model.

In section 6 we validated the estimated model and assessed the predictive potential of the covariates using three methods: bootstrap sampling with replacement, Wald tests, and a measure of discrimination. Results confirm that including rating specific covariates in a model is vital and that the macro-economic covariates are more influential in rating downgrade models.

Our results represent a first attempt to build a survival analysis model that explains rating migrations for financial institutions. Future research is needed and should endeavor to create a highly predictive model to forecast rating events.

Acknowledgments

We extend our gratitude to the Flemish Research Council (Odysseus grant B.0915.09) and the National Bank of Belgium (NBB/10/006 and NBB/11/004) for financial support.

References

Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The Journal of Finance*, *23*, 589—-609.

Altman, E. I., & Kao, D. L. (1992). Rating Drift in High-Yield Bonds. *The Journal of Fixed Income*, *1*, 15–20.

Bangia, A., Diebold, F. X., Kronimus, A., Schagen, C., & Schuermann, T. (2002). Ratings migration and the business cycle, with application to credit portfolio stress testing. *Journal of Banking & Finance*, *26*, 445–474.

Beaver, W. H. (1966). Financial Ratios As Predictors of Failure. *Journal of Accounting Research*, *4*, 71—-111.

Christensen, J. H., Hansen, E., & Lando, D. (2004). Confidence sets for continuous-time rating transition probabilities. *Journal of Banking & Finance*, *28*, 2575–2602.

Cox, D. R. (1972). Regression Models and Life-Tables. *Journal of the Royal Statistical Society. Series B (Methodological)*, *34*, 187–220.

Efron, B. (1977). The Efficiency of Cox's Likelihood Function for Censored Data. *Journal of the American Statistical Association*, *72*, 557– 565.

Figlewski, S., Frydman, H., & Liang, W. (2012). Modeling the effect of macroeconomic factors on corporate default and credit rating transitions. *International Review of Economics & Finance*, *21*, 87–105.

Frydman, H., & Schuermann, T. (2008). Credit rating dynamics and Markov mixture models. *Journal of Banking & Finance*, *32*, 1062–1075.

Hamilton, D. T., & Cantor, R. (2004). Rating Transition and Default Rates Conditioned on Outlooks. *The Journal of Fixed Income*, *14*, 54–70.

Hosmer, D. W., Lemeshow, S., & May, S. (2008). *Applied Survival Analysis*. Wiley-Interscience.

Hu, Y.-T., Kiesel, R., & Perraudin, W. (2002). The estimation of transition matrices for sovereign credit ratings. *Journal of Banking & Finance*, *26*, 1383–1406.

Jafry, Y., & Schuermann, T. (2004). Measurement, estimation and comparison of credit migration matrices. *Journal of Banking & Finance*, *28*, 2603–2639.

Jarrow, R. A., Lando, D., & Turnbull, S. M. (1997). A Markov Model for the Term Structure of Credit Risk Spreads. *The Review of Financial Studies*, *10*, 481—-523.

Kalbfleisch, J. D., & Prentice, R. L. (2002). *The Statistical Analysis of Failure Time Data*. Wiley-Interscience.

Kavvathas, D. (2000). Estimating Credit Rating Transition Probabilities for Corporate Bonds.

Kent, J. T., & O'Quigley, J. (1988). Measures of Dependence for Censored Survival Data. *Biometrika*, *75*, 525–534.

Kiefer, N. M., & Larson, C. E. (2007). A simulation estimator for testing the time homogeneity of credit rating transitions. *Journal of Empirical Finance*, *14*, 818–835.

Klein, J. P., & Moeschberger, M. L. (2003). *Survival Analysis: Techniques for Censored and Truncated Data*. (2nd ed.).

Kullback, S., & Leibler, R. A. (1951). On Information and Sufficiency. *The Annals of Mathematical Statistics*, *22*, 79–86.

Lando, D., & Skø deberg, T. M. (2002). Analyzing rating transitions and rating drift with continuous observations. *Journal of Banking & Finance*, *26*, 423–444.

Lane, W. R., Looney, S. W., & Wansley, J. W. (1986). An application of the cox proportional hazards model to bank failure. *Journal of Banking & Finance*, *10*, 511–531.

Martin, D. (1977). Early warning of bank failure A logit regression approach. *Journal of Banking & Finance*, *1*, 249—-276.

Nickell, P., Perraudin, W., & Varotto, S. (2000). Stability of rating transitions. *Journal of Banking & Finance*, *24*, 203–227.

O'Quigley, J., Xu, R., & Stare, J. (2005). Explained randomness in proportional hazards models. *Statistics in medicine*, *24*, 479–89.

Royston, P. (2006). Explained variation for survival models. *Stata Journal*, *6*, 83–96.

Royston, P., & Sauerbrei, W. (2004). A new measure of prognostic separation in survival data. *Statistics in medicine*, *23*, 723–48.

Sinkey, J. F. (1975). A Multivariate Statistical Analysis of the Characteristics of Problem Banks. *The Journal of*

Finance, *30*, 21—-36.

Trück, S. (2008). Forecasting credit migration matrices with business cycle effectsa model comparison. *The European Journal of Finance*, *14*, 359–379.

Whalen, G. (1991). A Proportional Hazards Model of Bank Failure : An Examination of Its Usefulness as an Early Warning Tool. *Economic Review from Federal Reserve Bank of Cleveland*, *Q1*, 21—-31.