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An Examination of Rating Corporate Bonds Through the Cycle

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Rating Through the Cycle

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Abstract

Changing credit rating migration intensities over the business cycle has been the subject of numerous studies (for example, Nickell et al. (2000) and Bangia et al. (2002)). Standard & Poor's, however, asserts that credit ratings are based on through the cycle measures; meaning that changes in the default risk should affect an issuer's credit rating only if these changes are persistent. Short-term fluctuations in default risk, such as a recession or uncharacteristic asset write-offs, should not affect the credit rating. Through an adaptation of a runs test and smoothed intensity estimates, we are able to demonstrate that the baseline downgrade intensity of Evans (2007) is not constant, and thus reject the policy of rating through the cycle.

The rejection of rating through the cycle has asset management ramifications. A consequence of non-constant baseline downgrade intensities is that there are systemic risks of credit re-evaluations that cannot be neutralised by large diversified debt portfolios. Where there is a strong relationship between debt value and credit rating, the sustenance of portfolios because of finite debt maturity means that industry- or economy-wide fluctuations in migrations intensities can result in large realised losses. Furthermore, systemic downgrade risks have implications for a bank's compliance with the Basel II Accord, where quality restrictions for capital provisions are in place.

Keywords: credit migrations; rating through the cycle; issuer correlation; baseline intensity.

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1. introduction

The primary motivation of this paper is to use the baseline intensity to examine a contentious rating agency policy, that of rating corporate bonds *through the cycle*. Standard & Poor's Corporate Ratings Criteria (Standard & Poor's, 2006, pg. 33) stresses the forward-looking nature of credit ratings and therefore cyclical behaviour, such as industry or macroeconomic business cycles, should not directly affect an issuer's credit rating. Standard & Poor's justification is that

> there is no point in assigning high ratings to a company enjoying peak prosperity if that performance level is expected to be only temporary. Similarly, there is no need to lower ratings to reflect poor performance as long as one can reliably anticipate that better times are just around the corner. (Standard & Poor's, 2006, pg. 34)

This policy should result in

> . . . the observed rates of default in any period for Standard & Poor's ratings will vary over time and for different sectors depending on where a particular industry is within the economic cycle. (Standard & Poor's Risk Solutions, 2006, pg. 4)

By Standard & Poor's definition, cyclical behaviour embraces financial risks, business risks and rating policy. Thus, cyclical behaviour of an issuer's financial data, such as sales or net income, should not affect credit rating migrations. It is difficult to distinguish between temporary and persistent changes in an issuer's finances, with Standard & Poor's conceding that this policy is difficult to maintain because of the unpredictability of business cycles, so an analysis of rating through the cycle is an analysis of Standard & Poor's aspirations rather than their steadfast assertions (Standard & Poor's Risk Solutions, 2006). This does not make such an analysis worthless; whether Standard & Poor's achieves rating through the cycle is important for establishing model assumptions and crucial in accounting for systemic risks in portfolio management.

At present, little research directly investigates the policy as stated by Standard & Poor's above. For example, Amato and Furfine (2004) find support for rating through the cycle, but they control for cyclical business and financial risks, and thus any finding is a reflection of rating policy alone. Feng et al. (2008) reject rating through the cycle, and we aim to further their conclusions by controlling for issuer-specific effects. Whilst not addressing the policy of rating through the cycle directly, Nickell et al. (2000) and Bangia et al. (2002) show that migration probabilities are time heterogeneous. Furthermore, Trück (2005) and Parnes (2007) demonstrate a correlation between macroeconomic covariates and credit rating migration probabilities.

We adopt the directional multiplicative intensity model by Evans (2007). Specifically, we model the intensity process of a downgrade or upgrade (directional migration) from an issuer's current credit rating. Consider a simplified example of an issuer with credit rating

AA: In previous studies, this issuer would have a probability or intensity of migrating to any other credit rating, each one needing to be estimated and tested individually. Modifying the approach of Evans (2007), this issuer has intensities for an upgrade, downgrade and default from AA. A directional migration intensity has two components—a baseline directional migration intensity and a relative risk function. A baseline intensity is the downgrade or upgrade intensity common to all issuers in a stratum (in our case, this stratum is an industry sector). A relative risk function scales this intensity up or down according to an individual issuer's riskiness. Whereas Evans (2007) focuses on the latter of these components, we intend to analyse the former. The directional multiplicative intensity model improves on previous research in examining rating through the cycle because we are able to control for the issuer-specific effects through the relative risk function before modelling the baseline intensity.

An understanding of the dynamics behind the baseline intensity is necessary to appreciate the systemic risks of a corporate bond. While issuer-specific risks are diversifiable, it is more difficult to manage risks shared by all issuers. The baseline intensities capture these systemic risks, since these are the risks common to all issuers in a stratum. An intensity model with an unspecified baseline intensity such as those fit by Evans (2007) is useful in making decisions between assets and measuring issuer-specific risks, but the baseline intensity requires specification to model an issuer over time. If an asset management regime imposes a target default rate or credit-quality restrictions for capital adequacy (such as investment grade assets only) then the absolute migration probabilities are necessary. More recently, the Basel II Accord encourages the appreciation of systemic risks (Basel, 2004, paragraph 503).

Rating through the cycle is analogous to basing assessment on a long-term default rate (Feng et al., 2008). Temporary effects on the issuer—whether internal or external—do not change the credit rating. In addition, Standard & Poor's aim to maintain the long-term default rate from a credit rating constant over time (Standard & Poor's Risk Solutions, 2006). In the context of the directional multiplicative intensity model, these imply that the baseline intensities are approximately constant through time. If an issuer's credit rating is not dependent on an industry's economic cycle, economic shocks or other common temporary risks, then the cause of a credit rating migration must be issuer-specific. Furthermore, by Standard & Poor's definition, the cause of a credit rating migration must be both persistent (non-cyclical) and issuer-specific. We test this implication by observing the baseline intensities of our models. While previous studies attempt to capture rating through the cycle, the directional multiplicative intensity model is better placed to account for issuer-specific effects without needing to directly specify and model business cycle effects.

Controlling for the persistent issuer-specific effects refers to their appearance in the relative risk function. Recall, the directional component of the migration model is a stratum-specific intensity scaled by an issuer-specific relative risk function. Using the relative risk function to reflect persistent issuer-specific information leaves the subsequently estimated baseline intensity reflecting cyclical and systemic risks. If a control for persistent issuer-specific effects is not used, implying a Markovian model (for examples, see Nickell et al. (2000) and Bangia et al. (2002)), then a fluctuation in the migration intensity estimates may be due to an aggregate change in the risk profiles of issuers.

We complete two sets of analyses. Firstly, we complete an analysis using the demographic effects of Lando and Skødeberg (2002) and Evans (2007). The motivation here is to create a model controlled for basic credit rating demographics; the time since entry and the mode of entry into a credit rating (momentum and excitability). These effects are convenient because we do not consider issuer-specific information except that generated by the credit rating process itself. This model does not endorse or condemn rating through the cycle, since Standard & Poor's use other information in determining credit ratings. Regardless, the demography-controlled model has the advantage of abundant data for a comprehensive model and remains informative if asset management were to occur using only issuers' credit rating processes. Moreover, it enables us to confirm industry heterogeneity in the baseline intensities. Secondly, we analyse the baseline intensity after controlling for persistent issuer-specific financial and business information. If this information adequately summarises the data Standard & Poor's uses for determining credit ratings, the resulting baseline intensities will reflect the systemic risks retained in the migration intensities by Standard & Poor's. Unfortunately, we do not have a clear understanding of how data affects Standard and Poor's determination, or even access to this data in a timely manner. We use the equity market as a proxy for determining a persistent change in an issuer's financial and business risks (for the stock markets anticipation of credit rating migrations, see Hsueh and Liu (1992)). We propose that the equity market's relative assessment of an issuer compared to other issuers should correspond to persistent changes in the issuer's financial or business risks. This market-reaction model is a simple and appropriate representation of Standard & Poor's policy.

The approximation of baseline directional migration intensities requires further exposition on the directional multiplicative intensity model, and visualisation requires the adoption of smoothing techniques. Industry stratification can often lead to dubious baseline intensity estimates for credit ratings with few migrations due to the spacing of migrations over time. Therefore, we combine the credit ratings into a rating grade to visualise fluctuations in baseline intensities. In addition, we must depart from a model assumption made by Evans (2007) because, unlike other downgrades, Standard & Poor's accept that the frequency of defaults fluctuate with the economic cycle (Koopman and Lucas, 2005). Thus, we fit our directional multiplicative intensity model with downgrades excluding migrations to default. We can think of an issuer as being subject to four competing risks; downgrade, upgrade, lateral migration and default. This amendment to Evans (2007) does not alter the coefficient estimates by a material degree.

By adapting the runs test (Benjamin and Pollard, 1992, pp. 233) and plotting smoothed estimates of non-parametric baseline intensity estimates, we observe cyclicality in many baseline intensities. The demography-controlled model rejects the independence of the baseline intensities over consecutive half-years for most credit ratings. An aggregated graphic representation of these baseline intensities show that migration intensities change over time after controlling for the effects of momentum and excitability. In addition, we see that the baseline intensities of industry sectors differ, as shown by Evans (2007).

Standard & Poor's does not attain the objective of rating through the cycle. Upon controlling for persistent risks using the market-reaction model, we reject baseline intensity constancy in most investment grade credit ratings and industrial et al. speculative grade credit ratings, advocating cyclical baseline intensities. Conclusions for the financial and utilities sectors are tempered, however, with merged data samples (from corporate debt and equity databases) reducing the effectiveness of the runs test and the interpretability of the smoothed baseline intensity estimates. Regardless, we show that baseline intensity constancy remains questionable.

This paper proceeds as follows. We begin in section 2 by discussing the data Standard & Poor's data available for our analyses. Next, we develop Evans' (2007) directional migration intensity model further, by deriving a baseline intensity estimate in section 3. This includes the specification of the runs test in subsection 3.2 and the smoothing using kernel functions in subsection 3.3. In section 4, we analyse the baseline intensity for demography-controlled models, and in section 5, we do so with market-reaction models. Possible future research is proposed in section 6 and our findings are summarised in section 7.

2. data

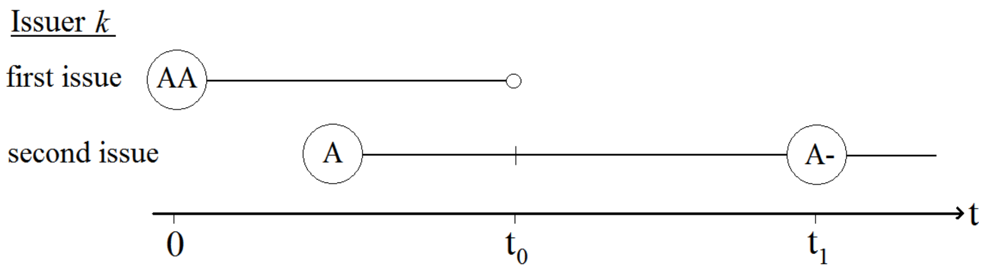
Credit rating data from Standard & Poor's rating agency are sourced from Mergent® Fixed Income Security Database (FISD). This database provides the categorisation of bond issues into rating classes based on the issuer's ability to service the debt, as determined by Standard & Poor's. All equity market data is sourced from the Centre for Research in Security Prices® US Stock Database (CRSP). Appendix A elaborates on the data used from FISD and CRSP.

We use Standard and Poor's credit rating data from 1 January 1997 to 31 December 2006. The credit ratings, from lowest to highest risk, are labelled AAA, AA+, AA, . . . , B-, CCC, CCC-, CC and C (see appendix B for rating definitions). We group the final three classes (CCC-, CC and C) into one class labelled CCC-. We refer to credit ratings AAA to BBB- as investment grade and BBB- to CCC- as speculative grade. Furthermore, this paper refers to default as an absorbing credit rating labelled D. We include the Not Rated class, labelled NR, but consider it neither higher nor lower than any other credit rating. The five industry classifications used by Standard and Poor's are industrial, financial, utilities, government and miscellaneous. We combine industrial, government and miscellaneous issuers into one group—industrial et al.

We have access to only issue credit ratings through FISD, but require issuer credit ratings because multiple issues from a single issuer corrupt the independent subject requirement of maximum likelihood estimation. Therefore, we allow only one issue for an issuer at any time, and treat the issues as representative of the issuer's credit rating. We contend that this method is acceptable because the drivers of a credit rating migration should not dramatically differ between the few close credit ratings that an issuer's issues can reside, and we intend to quantify these drivers. Upon maturity, we exchange the representative issue for another, but we do not treat this as a migration if the new issue has a different credit rating. We demonstrate this procedure in figure 1, where issuer k's first issue is right-censored on maturity at time t_0 and the second issue downgrades one credit ratings at t_1. In this example, issuer k is has credit rating AA until t_0, A between t_0 and t_1, and migrates from A to A- at t_1 and is in A- from thereon. The second issue is left-truncated at t_0 and prior information is discarded.

Our demography-controlled model requires that we exclude an issuer's experience up to

Figure 1: An example of right-censoring and left-truncation using hypothetical issuer k with two issues



the first migration, and the market-reaction model requires the merging of the FISD and CRSP databases. Both of these procedures reduce the sample size. The original Standard & Poor's sample statistics and the percentage available for each model are in appendix A.2

3. baseline directional migration intensity

We begin our formulation of the migration intensities with the states representative of the ordered credit ratings as determined by Standard & Poor's; AAA is the highest state (with the lowest risk) and CCC- is the lowest state. The Not Rated state and the Default state are treated as neither higher nor lower than other states, with migrations to and from the Not Rated and Defaults states treated as *lateral* migrations. (This is a departure from Evans (2007), who assumes default to be a downgrade.)

The multivariate counting process $\mathbf{N}_{ij,\ell} = (N_{ij,k\ell}\ ; k = 1, \cdots, m_\ell)$ counts each migration from state i to state j of each issuer in stratum $\ell = \{1, \cdots, M\}$, where M is the number of strata and m_ℓ is the number of issuers in stratum ℓ. The *full migration intensity* is the rate at which an issuer migrates between two specific credit ratings; often referred to as a hazard rate. Assuming unique migration times from state i within stratum ℓ, we define

$$d\Lambda_{ij,k\ell}(t) = \mathbb{E}[dN_{ij,k\ell}(t)|\mathcal{F}_{t^-}, \mathcal{G}_{t^-}]$$

as the full migration intensity (Andersen and Gill, 1982) where

$$dN_{ij,k\ell}(t) = \lim_{dt \searrow 0}(N_{ij,k\ell}(t^- + dt) - N_{ij,k\ell}(t^-)).$$

$\Lambda_{ij,k\ell}(t)$ is the cumulative intensity process for issuer k migrating to state j from i. $\{\mathcal{F}_t\}_{t\geq 0}$ is the appropriate filtration generated by the process up to time t, and $\{\mathcal{G}_t\}_{t\geq 0}$ is an ancillary information process containing information not dependent on the credit rating process but relevant to the issuer up to time t.

Consider the directional multiplicative intensity model from Evans (2007) where the migration is from i in direction d, where d is the set of credit ratings j either *up*, *down*, *default* or *lateral* from the current state i. It contains a relative risk function $(Y_{i,k\ell}(t) \exp\{\boldsymbol{\beta}'_{id}\mathbf{X}_k(t)\})$, a baseline directional intensity $(\Lambda_{d|i,0\ell}(t))$ and a conditional destination mass function $(p_{j|id,\ell}(t))$. We express this as

$$d\Lambda_{ij,k\ell}(t) = Y_{i,k\ell}(t) \exp\left\{\boldsymbol{\beta}'_{id}\mathbf{X}_k(t)\right\} d\Lambda_{d|i,0\ell}(t)p_{j|id,\ell}(t),$$

where $d\Lambda_{d|i,0\ell}(t)/dt$ is non-negative with $\int_0^t d\Lambda_{d|i,0\ell}(t) < \infty$ for all t. This paper considers the baseline directional intensity, but we require the relative risk function to estimate this intensity.

The unconditional likelihoods of these intensity processes are

$$\mathcal{L}(d\Lambda_{d|i,0\ell}, \boldsymbol{\beta}_{id}, p_{j|id,\ell}) = \prod_t \left(\prod_{\ell kj} \left(Y_{i,k\ell}(t) \exp\left\{ \boldsymbol{\beta}'_{id} \mathbf{X}_k(t) \right\} d\Lambda_{d|i,0\ell}(t) p_{j|id,\ell}(t) \right)^{dN_{ij,k\ell}(t)} \right)$$
$$\times \exp\left(-\sum_\ell \int_t \sum_k \sum_j Y_{i,k\ell}(s) \exp\left\{ \boldsymbol{\beta}'_{id} \mathbf{X}_k(s) \right\} d\Lambda_{d|i,0\ell}(s) p_{j|id,\ell}(s) \right), \qquad (1)$$

where $\tilde{N}_{id,k\ell}$, is proposed to count d-migrations, where

$$\tilde{N}_{id,k\ell}(t) = \sum_{j \in d} N_{ij,k\ell}(t)$$

is the total number of migrations in direction d from state i for issuer k up to time t.

Evans (2007) demonstrates that the partial likelihood estimate of $\boldsymbol{\beta}_{id}$ can be found independently of $p_{j|id,\ell}$ (appendix C.1). While applying partial likelihood estimation, Evans (2007) mentions that an attractive property of the directional multiplicative intensity model is that likelihood of $d\Lambda_{ij,k\ell}$ is maximised by maximising the likelihoods of $p_{j|id,\ell}$ and $d\Lambda_{d|i,k\ell}$ independently. We can show, using equation 1, that this is indeed the case, with

$$\begin{aligned}
\mathcal{L}(d\Lambda_{d|i,0\ell}, \boldsymbol{\beta}_{id}, p_{j|id,\ell}) &= \mathcal{L}_1(d\Lambda_{d|i,0\ell}, \boldsymbol{\beta}_{id}) \mathcal{L}_2(p_{j|id,\ell}) \\
&= \left(\prod_{t\ell kj} p_{j|id,\ell}(t)^{dN_{ij,k\ell}(t)} \right) \\
&\times \prod_t \left(\prod_{\ell k} \left(Y_{i,k\ell}(t) \exp\left\{ \boldsymbol{\beta}'_{id} \mathbf{X}_k(t) \right\} d\Lambda_{d|i,0\ell}(t) \right)^{d\tilde{N}_{id,k\ell}(t)} \right) \\
&\times \exp\left(-\sum_\ell \int_t \sum_k Y_{i,k\ell}(s) \exp\left\{ \boldsymbol{\beta}'_{id} \mathbf{X}_k(s) \right\} d\Lambda_{d|i,0\ell}(s) \right),
\end{aligned} \qquad (2)$$

since $\sum_j p_{j|id,\ell}(t) = 1$.

Thus, $dN_{ij,k\ell}(t)$ and $d\tilde{N}_{id,k\ell}(t)$ both have Poisson interpretations,

$$\begin{aligned}
dN_{ij,k\ell}(t) &\sim Poisson(Y_{i,k\ell}(t) \exp\left\{ \boldsymbol{\beta}'_{id} \mathbf{X}_k(t) \right\} d\Lambda_{d|i,0\ell}(t) p_{j|id,\ell}(t)) \\
d\tilde{N}_{id,k\ell}(t) &= \sum_j dN_{ij,k\ell}(t) \\
&\sim Poisson(Y_{i,k\ell}(t) \exp\left\{ \boldsymbol{\beta}'_{id} \mathbf{X}_k(t) \right\} d\Lambda_{d|i,0\ell}(t)).
\end{aligned}$$

3.1. non-parametric estimation

We look first to consider non-parametric maximum likelihood estimation to define the baseline directional migration intensity. This is an important advancement on Evans

(2007), who examines only the relative risk components of the directional multiplicative intensity model. We must assume that, in non-parametric estimation, $\Lambda_{d|i,0\ell}$ jumps only when $\tilde{N}_{id,k\ell}$ jumps, leaving $\Delta\Lambda_{d|i,0\ell}(t^*) \geq 0$ and $\Delta\tilde{N}_{id,k\ell}(t^*) \geq 0$ for every d-migration time t^* and zero otherwise. Thus, adapting equation 2, we have

$$\begin{aligned}\mathcal{L}(\Delta\Lambda_{d|i,0\ell}, \boldsymbol{\beta}_{id}, p_{j|id,\ell}) = &\left(\prod_{t^*\ell kj} p_{j|id,\ell}(t^*)^{\Delta N_{ij,k\ell}(t^*)}\right) \\ &\times \prod_{t^*}\left(\prod_{\ell k}\left(Y_{i,k\ell}(t^*)\exp\left\{\boldsymbol{\beta}'_{id}\mathbf{X}_k(t^*)\right\}\Delta\Lambda_{d|i,0\ell}(t^*)\right)^{\Delta\tilde{N}_{id,k\ell}(t^*)}\right) \\ &\times \exp\left(-\sum_{\ell}\sum_{t^*}\sum_{k} Y_{i,k\ell}(t^*)\exp\left\{\boldsymbol{\beta}'_{id}\mathbf{X}_k(t^*)\right\}\Delta\Lambda_{d|i,0\ell}(t^*)\right). \qquad (3)\end{aligned}$$

We aim to find the non-parametric maximum likelihood estimate of the jump function $\Delta\Lambda_{d|i,0\ell}(t^*)$ at some migration time s^* and in some stratum l, $\Delta\Lambda_{d|i,0l}(s^*)$. The first derivative with respect to $\Delta\Lambda_{d|i,0l}(s^*)$ of the logarithm of equation 3 is

$$\frac{\partial ln\mathcal{L}(\Delta\Lambda_{d|i,0\ell}, \boldsymbol{\beta}_{id}, p_{j|id,\ell})}{\partial\Delta\Lambda_{d|i,0l}(s^*)} = \frac{\sum_k \Delta\tilde{N}_{id,kl}(s^*)}{\Delta\Lambda_{d|i,0l}(s^*)} - \sum_k Y_{i,kl}(s^*)\exp\left\{\boldsymbol{\beta}'_{id}\mathbf{X}_k(s^*)\right\}, \qquad (4)$$

and the second derviative is

$$\frac{\partial^2 ln\mathcal{L}(\Delta\Lambda_{d|i,0\ell}, \boldsymbol{\beta}_{id}, p_{j|id,\ell})}{\partial\Delta\Lambda_{d|i,0l}(s^*)^2} = \frac{-\sum_k \Delta\tilde{N}_{id,kl}(s^*)}{\Delta\Lambda_{d|i,0l}(s^*)^2}. \qquad (5)$$

By setting equation 4 to zero we find the maximum likelihood estimate of $\Delta\Lambda_{d|i,0l}(s^*)$ conditioned on $\boldsymbol{\beta}_{id}$ as

$$\Delta\hat{\Lambda}_{d|i,0l}(s^*;\boldsymbol{\beta}_{id}) = \frac{\sum_k \Delta\tilde{N}_{id,kl}(s^*)}{\sum_k Y_{i,kl}(s^*)\exp\left\{\boldsymbol{\beta}'_{id}\mathbf{X}_k(s^*)\right\}},$$

which is an adaptation of the Nelson-Aalen estimate, often called the Breslow estimate (Breslow, 1974).

Extending this to create our non-parametric continuous step function for the cumulative baseline directional migration intensity for any stratum, subsequent to estimating $\boldsymbol{\beta}_{id}$, we have

$$\hat{\Lambda}_{d|i,0\ell}(t;\hat{\boldsymbol{\beta}}_{id}) = \int_0^t \frac{J_{i\ell}(s)d\tilde{N}_{id,\cdot\ell}(s)}{\sum_k Y_{i,k\ell}(s)\exp\left\{\hat{\boldsymbol{\beta}}'_{id}\mathbf{X}_k(s)\right\}}, \qquad (6)$$

where $J_{i\ell}(t) = \mathbb{1}_{\{\sum_k Y_{i,k\ell}(t)>0\}}$ (with $0/0 = 0$) and $\sum_k d\tilde{N}_{id,k\ell}(t) = d\tilde{N}_{id,\cdot\ell}(t)$.

Any inference on the Breslow estimate is under an assumption that $\boldsymbol{\beta}_{id} = \hat{\boldsymbol{\beta}}_{id}$; we assume coefficient estimates are deterministic. Since $\hat{\boldsymbol{\beta}}_{id}$ has a margin for error, we confine our analyses to those credit ratings where we are confident in the accuracy of $\hat{\boldsymbol{\beta}}_{id}$. For a Breslow estimate to qualify for further inference, we require that the relative risk function containing $\hat{\boldsymbol{\beta}}_{id}$ be a statistically significant improvement over a relative risk function where $\boldsymbol{\beta}_{id} = \mathbf{0}$. This ensures that the relative risk function adequately contributes to the understanding of the migration intensities and does not distort the baseline intensity.

We estimate $\boldsymbol{\beta}_{id}$ via partial likelihood estimation, with the procedure given in appendix C.1 and the results in appendices C.2 and C.3. These results are similar to those found in Evans (2007).

3.2. runs test

We adapt the runs test (Wald and Wolfowitz, 1940) to compare our observed baseline intensity to an assumption of baseline intensity constancy. Consider the time interval $(0, \tau]$ under baseline intensity constancy, increments

$$\int_t^{t+s} d\Lambda_{d|i,0\ell}(r; \hat{\boldsymbol{\beta}}_{id})$$

and

$$\int_u^{u+s} d\Lambda_{d|i,0\ell}(r; \hat{\boldsymbol{\beta}}_{id})$$

are independent provided $t + s \leq u$, and

$$\mathbb{P}\left[\int_t^{t+s} d\Lambda_{d|i,0\ell}(r; \hat{\boldsymbol{\beta}}_{id}) - c > 0\right] = \mathbb{P}\left[\int_u^{u+s} d\Lambda_{d|i,0\ell}(r; \hat{\boldsymbol{\beta}}_{id}) - c > 0\right]$$

for any constant c. Thus,

$$S_c(t, t+s) = \begin{cases} 1 & \text{for } \int_t^{t+s} d\hat{\Lambda}_{d|i,0\ell}(u; \hat{\boldsymbol{\beta}}_{id}) > c \\ 0 & \text{otherwise} \end{cases}$$

for each interval $(0, s), (s, 2s), \ldots, (\tau - s, \tau)$ are independent also.

Given some c, we observe $n_+ = \sum_{u=0}^{\tau/s-1} S_c(us, us+s)$ positive deviations from c and $n_- = \tau/s - n_+$ non-positive deviations. We denote the number of groups of consecutive positive deviations as G_+ with observation g_+ (where $g_+ \leq min(n_+, n_- + 1)$). Under an assumption of baseline intensity constancy, the sequence of positive and non-positive deviations should be random. Our test statistic is based on the probability of observing as few groups as g_+ if the arrangement of n_+ positive and n_- non-positive deviations is random.

The total number of distinct arrangements of n_+ positive and n_- non-positive deviations is

$$\binom{n_+ + n_-}{n_+} = \binom{n_+ + n_-}{n_-} = \frac{(n_+ + n_-)!}{n_+! n_-!}.$$

There are

$$\binom{n_+ - 1}{g_+ - 1} = \frac{(n_+ - 1)!}{(g_+ - 1)!(n_+ - g_+)!}$$

distinct ways n_+ positive deviations can be sorted into g_+ non-empty groups (Benjamin and Pollard, 1992, pp. 234). Furthermore, g_+ groups can be distributed between n_- non-positive deviations

$$\binom{n_- + 1}{g_+} = \frac{(n_- + 1)!}{g_+!(n_- + 1 - g_+)!}$$

distinct ways (it helps to think of allocating g_+ items into $n_- + 1$ possible positions). Thus, the number of distinct ways to obtain g_+ positive groups amongst n_+ positive and n_- non-positive deviations is

$$\binom{n_+ - 1}{g_+ - 1}\binom{n_- + 1}{g_+},$$

and the probability of obtaining no more than g_+ positive groups from n_+ positive and n_- non-positive deviations is

$$\begin{aligned}\mathbb{P}\left[G_+ \leq g_+\right] &= \sum_{x=1}^{g_+} \frac{\binom{n_+-1}{x-1}\binom{n_-+1}{x}}{\binom{n_++n_-}{n_+}} \\ &= \sum_{y=0}^{g_+-1} \frac{\binom{n_+-1}{y}\binom{n_-+1}{n_--y}}{\binom{n_++n_-}{n_+}},\end{aligned} \tag{7}$$

which is a cumulative hypergeometric distribution.

If the baseline intensity is not constant, and for appropriate c, we will see sustained periods of the intensity being above or below c. This creates fewer groups of consecutive positive (or non-positive) deviations than if each observed deviation were independent of the last. The hypergeometric distribution provides us with the probability of observing a particular arrangement of deviations, conditioned on the number of each deviation and that they are independently distributed.

We choose c such that, under a hypothesis of baseline intensity constancy,

$$\begin{aligned}&\mathbb{P}\left[\int_t^{t+s} d\hat{\Lambda}_{d|i,0\ell}(r;\hat{\boldsymbol{\beta}}_{id}) - c \leq 0\right] \geq 0.5, \text{ and}\\ &\mathbb{P}\left[\int_t^{t+s} d\hat{\Lambda}_{d|i,0\ell}(r;\hat{\boldsymbol{\beta}}_{id}) - c \geq 0\right] \geq 0.5.\end{aligned}$$

That is, the median value of the discrete set, where up to half of the baseline intensity increments exceed c. We adopt the median since it provides the best opportunity for an equal number of positive and non-positive deviations, giving the largest sample possible for the test. Due to the skewness of $\int_t^{t+s} d\Lambda_{d|i,0\ell}(u;\hat{\boldsymbol{\beta}}_{id})$, an adoption of the median for c does not necessarily result in $n_+ = n_-$ because the sample is more than half occupied by zeros for credit ratings with rare d-migrations, although the median still provides the most positive deviations in this case. Regardless, instances where $n_- > n_+$ rarely provide sensible results because they are often indicative of a low population *at risk* rather than a low migration intensity.

The definition of cyclicality is ambiguous and flexible—possibly defining a weak constraint of baseline intensity fluctuations of undefined length and size or a strong constraint of baseline intensity fluctuations being predictable and rhythmical. The runs test adopts the former definition, with both the numbers in a group and magnitude of the deviations irrelevant. Such a test is preferable since we do not impose functional restrictions on the baseline intensity behaviour. If the strong constraint of predictable and rhythmical baseline intensities is appropriate then the weak constraint still applies and the runs test remains applicable.

This paper deals with the identification of cyclicality, and does not fit common risks to quantify causation. Therefore, the runs test is ideal because it is unassumptive in its assessment of cyclicality. Common methods, such as examining autocorrelation coefficients with the Durbin-Watson d-statistics (Gujarati, 1995), require far more onerous assumptions. Firstly, constant autocorrelation coefficients test the strong constraint where fluctuations are rhythmical and predictable, and non-constant autocorrelation coefficients require much larger samples sizes than our experiment can provide. Secondly, most common tests of autocorrelation require the residuals (the deviations from a null hypothesis of independence) to be normally distributed—a property that the heavily skewed intensities fail to fulfil. Lastly, these tests impose a constant variance over the sample period; the runs test does not impose this restriction. Thus, we propose that the runs test is intuitively more suitable to assessing baseline intensity fluctuations of undefined length and size without unnecessary restrictions.

We refer to the runs of like deviations as clumping, with positive deviations observed in distinct clumps. The p-value of the runs test, testing the null hypothesis of the baseline intensity for subsequent periods being independent against the alternative hypothesis of clumping, is $\mathbb{P}\left[G_+ \leq g_+\right]$ (equation 7).

3.3. smoothed intensities

To show the baseline intensities graphically we use a Kernel function to find smooth baseline intensities between t_1 and t_2,

$$\hat{\lambda}^b_{d|i,0l}(t) = b^{-1} \int_{t_1}^{t_2} K_{di\ell}\left(\frac{t-s}{b}\right) d\hat{\Lambda}_{d|i,0l}(s; \hat{\boldsymbol{\beta}}_{id}), \tag{8}$$

where b is known as the bandwidth, which determines how far either side of a point is used when smoothing, and $b \leq t_1 < t_2 \leq \tau - b$. A larger bandwidth produces a smoother intensity but risks biasing the estimate.

Furthermore, we use the Epanechnikov kernel function (Epanechnikov, 1969),

$$K(x) = \begin{cases} 0.75(1-x^2) & \text{for } -1 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases};$$

a choice that differs little in results from most common kernel functions (Silverman, 1986, pg. 43).

The optimal bandwidth for smoothing a baseline intensity estimate, $b^*_{di\ell}$, is found by

$$b^*_{di\ell} = \arg\min_b MISE(\hat{\lambda}^b_{d|i,0l}(t)),$$

where $MISE(\hat{\lambda}^b_{d|i,0l}(t))$ is the mean integrated squared error (Silverman, 1986, pg. 40). We can express this as

$$\begin{aligned} MISE(\hat{\lambda}^b_{d|i,0l}(t)) &= \mathbb{E}\int_{t_1}^{t_2} \left(\hat{\lambda}^b_{d|i,0l}(t) - \lambda_{d|i,0l}(t)\right)^2 dt \\ &= \mathbb{E}\int_{t_1}^{t_2} \hat{\lambda}^b_{d|i,0l}(t)^2 dt - 2\mathbb{E}\int_{t_1}^{t_2} \hat{\lambda}^b_{d|i,0l}(t)\lambda_{d|i,0l}(t) dt \\ &+ \mathbb{E}\int_{t_1}^{t_2} \lambda_{d|i,0l}(t)^2 dt. \end{aligned} \tag{9}$$

We minimise equation 9 with respect to b by obtaining the first term through the estimates from equation 8, obtaining the second term by the approximately unbiased estimate

$$-2 \sum_{t^* \neq s^*} b^{-1} K_{di\ell} \left(\frac{t^* - s^*}{b} \right) \frac{\sum_k \Delta \tilde{N}_{id,kl}(t^*)}{\sum_k Y_{i,kl}(t^*) \exp\left\{ \boldsymbol{\beta}'_{id} \mathbf{X}_k(t^*) \right\}} \frac{\sum_k \Delta \tilde{N}_{id,kl}(s^*)}{\sum_k Y_{i,kl}(s^*) \exp\left\{ \boldsymbol{\beta}'_{id} \mathbf{X}_k(s^*) \right\}},$$

where both t^* and s^* are event times with $t_1 \leq t^* \leq t_2$ (Ramlau-Hansen, 1983), and noting that the final term in equation 9 is constant with respect to b. We use computation methods to minimise $MISE(\hat{\lambda}^b_{d|i,0l}(t)) - \mathbb{E} \int_{t_1}^{t_2} \lambda_{d|i,0l}(t)^2 dt)$ and thus find $b^*_{di\ell}$.

Rather than adopt linear ninety-five percent point-wise confidence bands, we—with the aid of the delta method and equation 5—assume that the natural logarithm of the estimator for $\lambda_{d|i,0l}(t)$ follows an asymptotic normal distribution, giving the confidence interval

$$\hat{\lambda}_{d|i,0l}(t) \exp\left\{ \frac{\pm 1.96}{\hat{\lambda}_{d|i,0l}(t)} b^{-2}_{di\ell} \int_{t_1}^{t_2} K_{di\ell} \left(\frac{t-s}{b_{di\ell}} \right)^2 \frac{d\hat{\Lambda}_{d|i,0l}(s)^2}{d\tilde{N}_{id,\cdot\ell}(s)} \right\}. \tag{10}$$

In addition to being aesthetically superior to linear confidence bands, since they cannot fall below zero, this transformation is an improvement when dealing with a small sample size (Bie et al., 1987).

4. demography-controlled model

We control the directional migration intensities for successive migrations being more probable in the same direction (momentum), and for more recently migrated issuers having higher migration intensities (excitability). Controlling for these causes of population heterogeneity delivers results similar to Lando and Skødeberg (2002) and Evans (2007). With the presence of momentum and excitability, a Markovian model (Nickell et al., 2000; Bangia et al., 2002) can be misleading because of possible demographic changes in the credit rating. For example, where a large proportion of issuers downgrade into a credit rating, momentum can explain a heightened downgrade intensity, with excitability further aggravating the intensity if these downgrades were recent. Where these population characteristics change over time, a basic migration matrix will fail to reflect the true migration intensities. Standard & Poor's (2007) show that upgrade and downgrade frequencies change over time, with, for example, over twice the percentage of issuers downgraded in 2002 as in 1997 (18.72% versus 7.82%). Given Standard & Poor's policy of rating through the cycle, this implies large demographic shifts within (by momentum and excitability) or between credit ratings. Furthermore, years of many (or few) upgrades or downgrades follow similar years; for which momentum or excitability are viable explanations.

Our demography-controlled model incorporates the demographic differences in a credit rating—momentum and excitability—as issuer-specific effects. We model momentum by defining the first element of $\mathbf{X}_k$ in equation 1 as

$$\mathbb{1}_{k,down}(t) = \begin{cases} 1 & \text{if the most recent migration at time } t \text{ was down} \\ 0 & \text{otherwise} \end{cases}$$

for downgrades, or

$$\mathbb{1}_{k,up}(t) = \begin{cases} 1 & \text{if the most recent migration at time } t \text{ was up} \\ 0 & \text{otherwise} \end{cases}$$

for upgrades, and excitability by defining the second element of $\mathbf{X}_k$ as $\log(t-t_k^*)\times\mathbb{1}_{k,down}(t)$ or $\log(t-t_k^*)\times\mathbb{1}_{k,up}(t)$ for downgrades or upgrades respectively, where t_k^* is the time of the most recent migration of issuer k.

This provides us with a simple model for credit rating migrations, where the credit rating process generates the only factors driving relative risk. We do not consider the financial state of an issuer in calculating migration intensities; this demography-controlled model provides a hypothetical example of the directional multiplicative intensity model in a research-free environment. Management of a portfolio of corporate bonds with scant regard for issuers' balance sheets is consistent with this hypothetical example. Importantly, the demography-controlled model does not provide any reflection on the policy of rating through the cycle, since Standard & Poor's conducts analyses of issuers' financial conditions. Appendix C.2 contains the coefficient estimates for relative risk functions of the demography-controlled model.

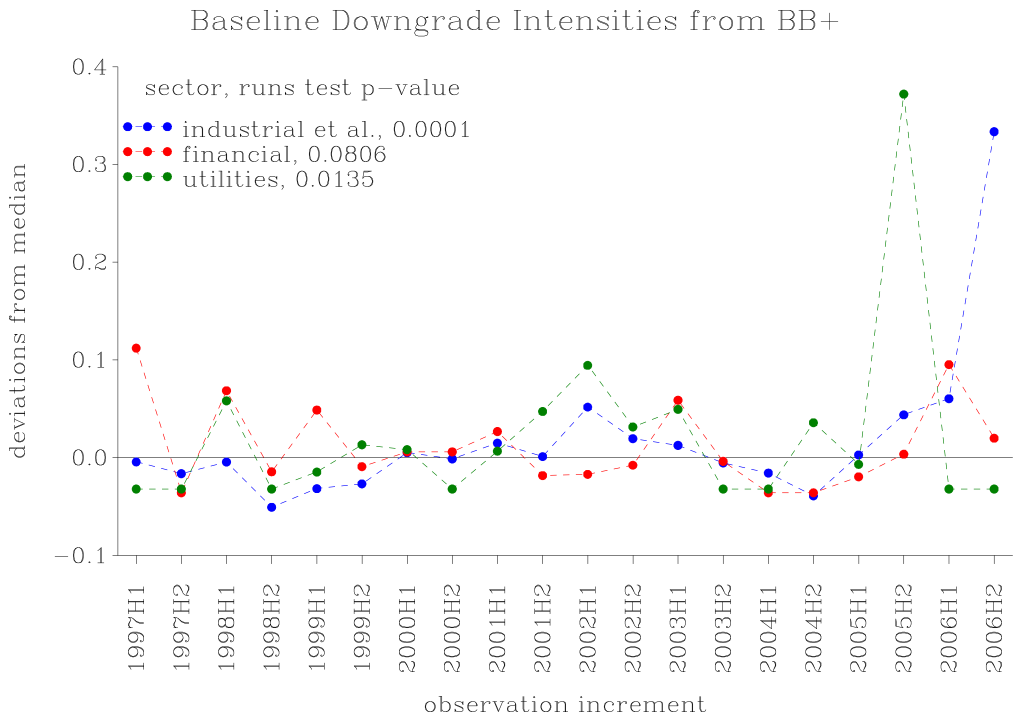
The demography-controlled model does account for possible distortions in baseline intensity estimates due to the demography of the issuers *at risk*. Therefore, the control for these demographic covariates is not trivial; the characteristics of the population of issuers in an industry sector with respect to these covariates changes over time. These demographic shifts invalidate Markovian models (or equivalently a directional migration intensity model with no issuer-specific effects) such as Bangia et al. (2002).

4.1. non-constancy of the demography-controlled baseline intensities

We perform the runs test from section 3.2 on the demography-controlled model to test weak cyclicality beyond demographic effects, and to demonstrate the strengths and weaknesses of the model before using it to test rating through the cycle in section 5.1. Furthermore, we provide impetus for the runs tests with an example of sample deviations and the autocorrelations estimates.

We adopt half-years for our observation increments over the ten years from 1 January 1997 to 31 December 2006; twenty deviations in total. The use of half-years is a compromise between economic and statistical significance, with the following considerations: Firstly, longer increments capture fundamental shifts in the baseline intensities rather than market noise, which is appropriate because broader economic cycles are usually in excess of a year. Thus, the runs test is unable to identify cyclicality with peaks and troughs of less than one year. This argument also applies against making increments too long, which may show no clumping because an entire cycle is within an increment. Secondly, strata with rare migrations require longer increments for the runs test to be effective, since shorter increment lengths increase the likelihood of no migrations in an increment, and thus consecutive positive deviations become unlikely even in years of heightened baseline intensity. Lastly, longer increments result in a smaller sample, reducing the ability to form meaningful conclusions (with possibly no combination of positive and negative deviations

Figure 2: Baseline Downgrade Intensity Deviations from Median for industrial et al., financial and utilities sectors for each half-year increment from 1997 to 1006 inclusive. In addition, we provide the p-values from the runs tests.

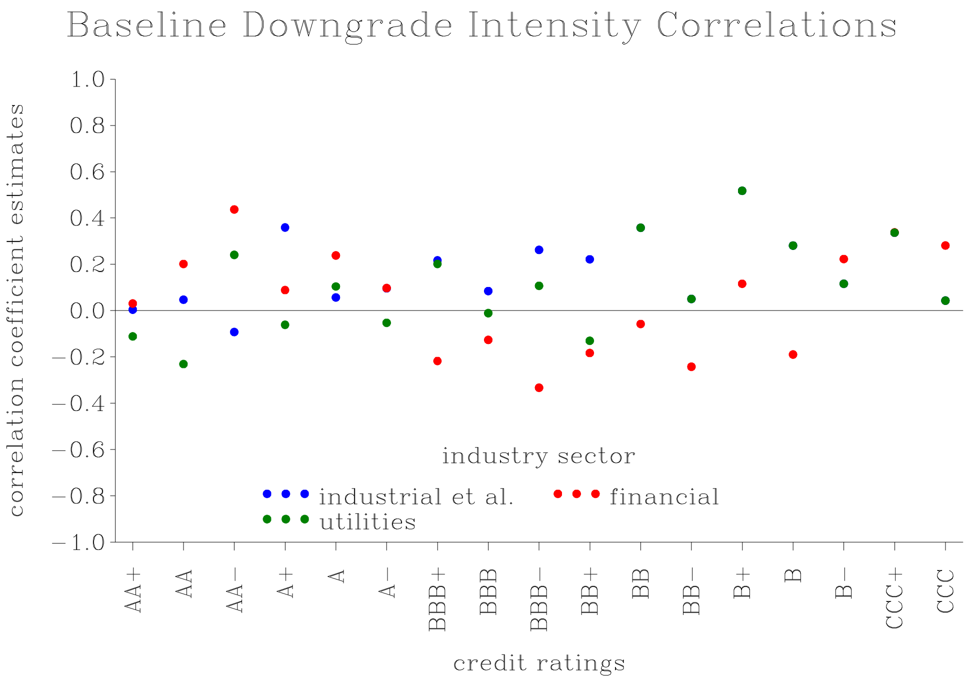


being too unlikely). Regardless, results hardly differ for increment lengths between one month and one year for the most populous credit ratings.

Figure 2 shows the observation increment deviations for downgrades from industrial et al., financial and utilities issuers in credit rating BB+. These deviations inform the runs test of cyclicality if the number of groups of positive deviations is improbable under an assumption of incremental independence. We see that the industrial et al. sector experiences long runs of positive and negative deviations, and the p-value from the runs test confirms this. The utilities sector also rejects baseline intensity incremental independence, although not as convincingly as the industrial et al. sector because the runs are shorter. We fail to reject the null hypothesis of incremental independence for the financial sector because the deviations oscillate between positive and negative for the first three years, although long runs in the later increments results in a p-value below ten percent.

Figure 3 summarises the dependence in successive observation increments showing the first-order autocorrelation statistics. Autocorrelation summarises the departure of successive random variables from independence. These correlation coefficient estimates are mainly positive with the exception of medium-risk financial sector downgrade intensities, meaning that a period of high baseline intensity is likely to precede another. On inspecting the example in figure 2, the negative correlation coefficient estimate for BB+ financial baseline downgrade intensity is unsurprising, given the oscillation of the deviations earlier in the sample period. The difference in estimates between credit ratings and industry sectors justifies the discrimination by these categories.

Figure 3: First-Order Autocorrelation Estimate of the Baseline Intensities for each industry sector, credit rating and migration direction over 1 January 1999 to 31 December 2004.



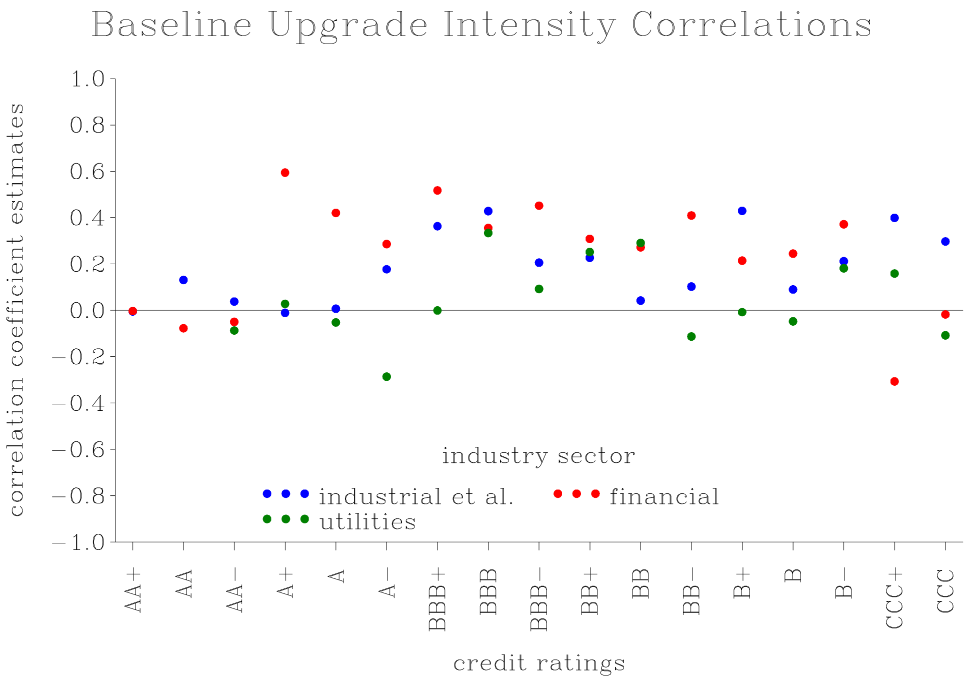


Table 1 contains the median, positive deviations (n_+), positive groups (g_+) and p-value for downgrades and upgrades in each credit rating and industry stratum. The number of positive deviations is usually ten—half of the sample. The number of positive deviations is less than ten when the median is zero, meaning migrations occur in less than half the observation increments. When there are ten positive deviations, any fewer than six positive groups will result in a rejection of the null hypothesis of independent increments. In any case, the results are unreliable when there are less then ten positive deviations. We qualify the experiment further by stating whether the relative risk function of the directional multiplicative intensity model is a statistically significant improvement on an empty relative risk (time-varying Markovian model). Where the improvement in unconvincing (Qualify? = N), we cannot be confident that the Breslow estimate requirement of $\boldsymbol{\beta}_{id} = \hat{\boldsymbol{\beta}}_{id}$ is met, and thus are sceptical of the legitimacy of the baseline intensity estimate.

We find that baseline intensity constancy is usually rejected in the most populous credit ratings and industry sectors (where the number of positive deviations is ten). Moreover, we usually observe six positive groups resulting in a p-value of eight percent when we are unable to reject the null hypotheses in the populous credit ratings. Downgrades in the industrial et al. sector shows statistically significant clumping for all credit ratings except A+ and A-. We observe similar significance with downgrades in the financial sector, with only BBB- and BB+ failing to reject baseline intensity constancy. While we can be confident in the results of the utilities sector in the investment grade credit ratings, very few issuers *at risk* in the earlier years leave the credibility of null hypotheses rejections in the speculative grade credit ratings under suspicion.

Similar suspicions are prevalent in the upgrades as well. Risky utilities sector issuers and very risky financial sector issuers are often among very few other issuers in their credit rating, meaning rejections of the null hypotheses may be symptomatic of the unreliability of the Breslow estimation (equation 6) rather than baseline intensities cyclicality. Regardless, the more populous credit ratings, where the median is greater than zero and the relative risk function improves on an empty model, argue strongly against the baseline intensity constancy with rejection or near-rejection in almost all instances.

We can conclude here that baseline intensity constancy is inappropriate when applying a demography-controlled model. Some factors other than momentum and excitability—either systemic and/or issuer-specific risks—change the baseline intensities over time. In addition, we see also that the runs test, although powerful and unassumptive for populous credit ratings, is flawed when we cannot rely on the Breslow estimate for the baseline intensity. This is sensible, since we cannot test if a process is cyclical if we cannot adequately estimate the process.

4.2. smoothed estimates of the demography-controlled baseline intensities

While the runs test rejects baseline intensity constancy in the well-populated credit ratings, it fails to illustrate the behaviour of these baseline intensities beyond clumping. In particular, contrasting the baseline intensities between industry sectors is impossible with the runs test. To compare these distinctions and for a visual appreciation of other behaviours, we fit optimised kernel functions to provide smooth baseline intensity estimates. The demography-controlled baseline intensity represents an issuer's directional migration

Table 1: Runs Test for the Demography-Controlled Model in each credit rating (i), migration direction and industry sector from 1 January 1997 to 31 December 2006. Each test includes the median baseline intensity estimate integrated over half-year increments, the number of positive deviations (n_+), the number of positive groups (g_+), and the probability of observing no more than g_+ positive groups among n_+ positive deviations under an assumption of increment independence (p-value). *Qualify?* indicates the statistical significance of the relative risk Model Fit (Y=yes, N=no).

Industry Sector		Industrial et al.			Financials			Utilities		
Rating (i)	Qualify?	median	$n_+ - g_+$	p-value	median	$n_+ - g_+$	p-value	median	$n_+ - g_+$	p-value
The Downgrade Migrations										
AA+	Y	0	8 − 3	0.001	0	9 − 4	0.004	0	2 − 2	1.000
AA	Y	0.097	10 − 5	0.013	0.076	10 − 4	0.001	0	4 − 4	1.000
AA-	Y	0.068	10 − 5	0.013	0.056	10 − 5	0.013	0.07	10 − 3	0.000
A+	Y	0.096	10 − 7	0.285	0.072	10 − 4	0.001	0.072	10 − 5	0.013
A	Y	0.074	10 − 3	0.000	0.038	10 − 5	0.013	0.097	10 − 5	0.013
A-	Y	0.092	10 − 6	0.081	0.036	10 − 4	0.001	0.069	10 − 5	0.013
BBB+	Y	0.072	10 − 5	0.013	0.039	10 − 5	0.013	0.049	10 − 5	0.013
BBB	Y	0.083	10 − 5	0.013	0.053	10 − 5	0.013	0.05	10 − 5	0.013
BBB-	Y	0.071	10 − 3	0.000	0.061	10 − 8	0.625	0.057	10 − 5	0.013
BB+	Y	0.051	10 − 3	0.000	0.036	10 − 6	0.081	0.032	10 − 5	0.013
BB	Y	0.082	10 − 4	0.001	0.064	10 − 5	0.013	0	9 − 4	0.004
BB-	Y	0.101	10 − 4	0.001	0.102	10 − 5	0.013	0	9 − 4	0.004
B+	Y	0.075	10 − 4	0.001	0.057	10 − 3	0.000	0	7 − 3	0.003
B	Y	0.084	10 − 3	0.000	0.099	10 − 5	0.013	0	9 − 4	0.004
B-	Y	0.123	10 − 5	0.013	0.048	10 − 4	0.001	0	3 − 3	1.000
CCC+	Y	0.155	10 − 3	0.000	0.091	10 − 4	0.001	0	7 − 4	0.035
CCC	Y	0.124	10 − 5	0.013	0.08	10 − 5	0.013	0	9 − 5	0.033
The Upgrade Migrations										
AA+	Y	0	6 − 2	0.000	0	1 − 1	1.000	0	0 − 0	−
AA	Y	0	5 − 3	0.051	0	2 − 2	1.000	0	0 − 0	−
AA-	N	0.022	10 − 6	0.081	0	4 − 4	1.000	0	2 − 2	1.000
A+	Y	0	9 − 5	0.033	0.034	10 − 4	0.001	0	6 − 3	0.011
A	Y	0.028	10 − 5	0.013	0.034	10 − 4	0.001	0	7 − 5	0.214
A-	N	0.041	10 − 6	0.081	0.062	10 − 4	0.001	0.035	10 − 5	0.013
BBB+	Y	0.032	10 − 5	0.013	0.054	10 − 4	0.001	0.017	10 − 7	0.285
BBB	Y	0.04	10 − 6	0.081	0.049	10 − 5	0.013	0.023	10 − 4	0.001
BBB-	Y	0.064	10 − 5	0.013	0.075	10 − 6	0.081	0.067	10 − 5	0.013
BB+	Y	0.079	10 − 6	0.081	0.083	10 − 5	0.013	0.082	10 − 5	0.013
BB	Y	0.081	10 − 6	0.081	0.094	10 − 7	0.285	0.157	10 − 4	0.001
BB-	Y	0.058	10 − 6	0.081	0.04	10 − 4	0.001	0	9 − 5	0.033
B+	N	0.088	10 − 4	0.001	0.056	10 − 3	0.000	0.108	10 − 6	0.081
B	Y	0.058	10 − 6	0.081	0.078	10 − 6	0.081	0	9 − 4	0.004
B-	Y	0.055	10 − 3	0.000	0	9 − 3	0.000	0	6 − 3	0.011
CCC+	Y	0.048	10 − 5	0.013	0	6 − 6	1.000	0	4 − 2	0.016
CCC	Y	0.081	10 − 4	0.001	0	5 − 4	0.372	0	2 − 2	1.000

intensity that is not attributable to momentum or excitability. Specifically, the baseline intensities reflect systemic risks, temporary and persistent changes in an issuer's business and financial risks, as well as changes to the rating agency policy.

Individually smoothed baseline intensity estimates are numerous and often similar in shape. We combine the baseline estimates for each credit rating into the investment and speculative grades to summarise the baseline intensity behaviour without burdensome results. We do not contend, however, that all issuers of the same rating grade experience the same baseline intensities—the contrary is demonstrably true—and so the weighted averaging of the baseline intensities is more complex than merging smoothed intensities. The average baseline intensities differ by credit ratings, but the fluctuations of the baseline intensities are similar by credit ratings. This is consistent with the lower credit ratings being riskier, but systemic risks affect the baseline intensities proportionally. Thus, we combine credit ratings by estimating aggregated Breslow estimates after controlling for each credit rating's relative risk function. Smoothing this estimate gives an approximation of the baseline directional migration intensity weighted by the reliability (measured by inverse variation) of each credit rating's contribution. This aggregation does not deliver the true baseline intensities, but does illustrate where common risks affect all credit ratings—the objective of this paper. In summary, we present figures in this section that reflect the relative behaviour of the baseline intensities over time, but do not capture the magnitude of an issuer's baseline intensity. This is only a minor concession because the baseline magnitude is difficult to interpret without knowing the make-up of the population's relative risks.

Recall, the Breslow estimate requires that $\boldsymbol{\beta}_{id} = \hat{\boldsymbol{\beta}}_{id}$. This assumption is dubious for credit ratings with low populations because the standard error of the estimate may be large. To avoid nonsensical graphics due to inaccurate relative risks distorting the baseline intensity estimates, we require that the log-likelihood ratios between the relative risk estimates and empty models (time-varying Markovian models) show the superiority of the fitted model with ninety-five percent confidence. Where this requirement is unmet, we exclude the credit ratings from the aggregated Breslow estimate and thus smoothed baseline intensity estimate. These Model Fit qualifications are in table 1 and the Model Fit statistics are in appendix C.2.

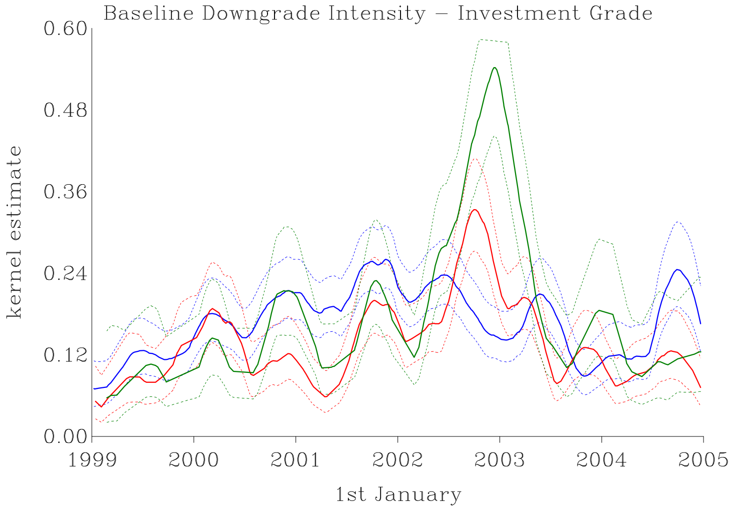
The optimal bandwidth to the nearest ten calendar days, as determined by minimising equation 9, varies between baseline intensities. We set a minimum bandwidth of one-hundred calendar days (approximately 69 business days) to ensure the smoothed intensity is representative of trends rather than localised fluctuations. Likewise, we set a maximum bandwidth of just under two years (approximately 483 business days) to ensure the estimates at that time are representative of the baseline intensity and the interval remaining for the graphic is sensible.

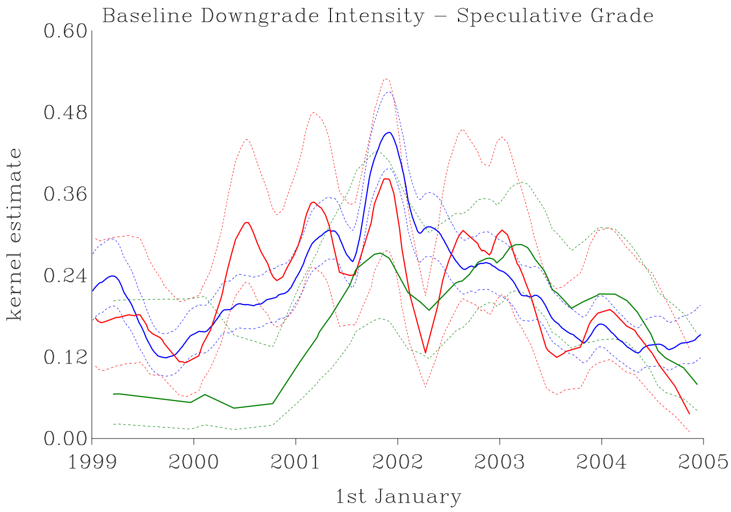
Figure 4 provides the smoothed baseline downgrade intensity estimates over six years from the 1 January 1999 to 31 December 2004, which ensures that all smoothed estimates can be calculated at the maximum bandwidth restriction. Each graph provides the smoothed estimates for industrial et al., financial and utilities issuers' baseline intensities, with a graph for downgrades from investment grade and speculative grade credit ratings. The shape is more important here than the magnitude because the relative risk function can scale the baseline intensity up or down by large multiples. While the smoothed baseline intensities allow us to appreciate the trends, we must consider the variance if we wish to judge whether such trends depict cyclicality or rogue observations. We include confidence bands around each smoothed estimate to demonstrate the interval of where the baseline intensity lies with ninety-five percent confidence. These confidence bands include the variability in the Breslow estimate and the subsequent smoothing, although they treat the issuer-specific coefficient estimates as deterministic. We occasionally truncate the 97.5 percent confidence band for the utilities sector downgrade intensities to allow adequate an adequate scale for interpretation.

We must be careful in drawing ambitious conclusions from these figures; we show only smoothed estimates of the baseline migration intensities, and judgements on the nature of the full migration intensities would require an incorporation of the issuer-specific information that these estimates are conditioned upon (see equation 6). These figures allow conclusions, however, on the systemic risks affecting migration intensities.

A constancy assumption for the baseline downgrade intensity appears improper in all

Figure 4: Smoothed Baseline Downgrade Intensity Estimates for the Demography-Controlled Model for each industry sector and rating grade from 1 January 1999 to 31 December 2004. The industrial et al. sector is blue, the financial sector is red and the utilities sector is green. Optimal bandwidths: investment grade (100,100,100); speculative grade (100,110,160).





industry sectors for investment grade and speculative grade issuers. We observe that these intensities differ between industry sectors, with estimates often moving beyond each other's confidence bands, but many fluctuations occur at the same time. For example, all issuers appear to experience heightened downgrade intensities in late 2002. This is consistent with the experiments of Giampieri et al. (2005), who observe that different industry sectors experience heightened default intensities at similar times. Also notable, is that one industry sector does not dominate, with each sector experiencing periods of the highest baseline downgrade intensity. This is crucial to our understanding of industry heterogeneity because it means that that industry-specific effects on the migration intensity are not proportional, confirming the use of Monte Carlo simulations by Evans (2007).

For the industrial et al. sector, we find that the baseline downgrade intensity estimates are not constant, or even piece-wise constant (which may occur with a Standard & Poor's policy change). Intensities in both investment grade and speculative grade credit ratings show heightened systemic risks from early 2001 to mid-2002. Otherwise, the downgrade intensities of these rating grades differ, with the investment grade issuers alone in suffering larger downgrade intensities in mid-2003 and late 2004, while the speculative grade issuers have heightened downgrade intensity in early 1999.

Financial issuers begin and end the period displayed with relatively low baseline downgrade intensities in investment grade and speculative grade credit ratings. While both rating grades show increased baseline downgrade intensities at similar times, an investment grade issuer experiences very high common risk at the end of 2002, whereas a speculative grade issuer's baseline downgrade intensity peaks at the end of 2001 after over a year of heightened common risks. Smaller sample sizes mean wider confidence bands in the speculative grade credit ratings, although we still discard an assumption of constant baseline downgrade intensities.

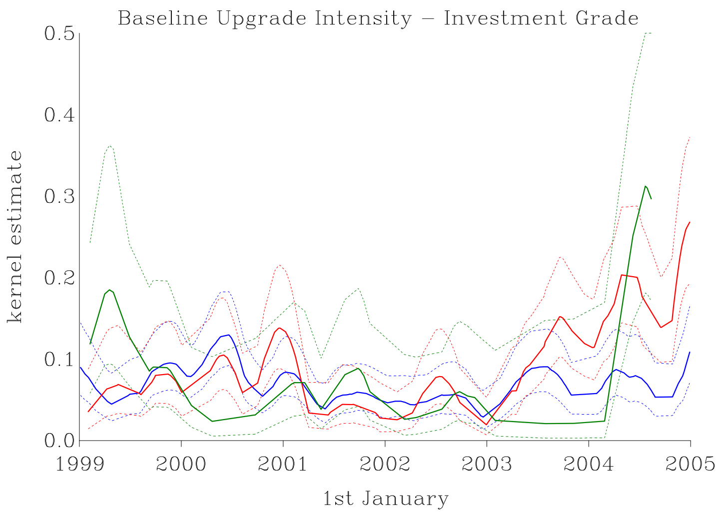
We have less confidence in the accuracy of utilities baseline downgrade intensities, although we remain able to reject constancy in both the investment grade and speculative grade. The wider confidence bands—particularly for speculative grade credit ratings—are a consequence of fewer issuers *at risk* and downgrading in these credit ratings. Although both rating grades show low migration intensities before 2001 and after 2003, the relative extremes of the heightened baseline intensities from 2001 to 2004 differ: the investment grade shows a severely exaggerated baseline downgrade intensity in late 2002; whereas the speculative grade is no riskier at this time than over the previous year.

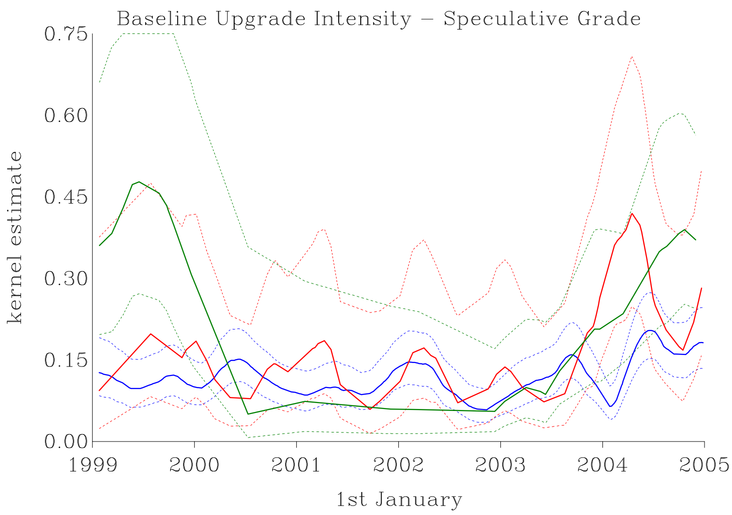
When comparing smoothed baseline upgrade migration intensities in figure 5, note that we have altered the scale of the vertical axis in each of the graphs to give a clearer picture. Regardless, the shape is more important here than the magnitude, since, as previously mentioned, the relative risk function can scale the baseline intensity up or down by large multiples. The smoothed baseline upgrade intensity estimates display less profound fluctuations than the downgrade intensities. For these smoothed estimates, we exclude credit ratings AA- and A- from the investment grade and credit rating B+ from the speculative grade because the relative risks are unreliable (see appendix C.2).

Industrial et al. and financial issuers have similar baseline intensities, with the smoothed estimates within each other's confidence bands until late 2003 in both rating grades. While this is not surprising in the speculative grade (because of the low population in the financial sector), the baseline intensities in the investment grades are accurate, and thus the similarities suggest industry homogeneity may be acceptable up to 2004. The smoothed estimates in the utilities sector are distinct from those in the industrial et al. and financial sectors, with higher upgrade intensities before 2000 and after 2003. Accuracy of the baseline upgrade intensities for speculative grade utilities issuers is poor, however, with few observations resulting in wide confidence bands.

The baseline upgrade intensities are similar in investment grade and speculative grade credit ratings over the middle of the observation period, with the estimates for all industry sectors ebbing from the middle of 2001 to the end of 2002. Although both rating grades show higher common risks at the end of the observation period, investment grade issuers

Figure 5: Smoothed Baseline Upgrade Intensity Estimates for the Demography-Controlled Model for each industry sector and rating grade from 1 January 1999 to 31 December 2004. The industrial et al. sector is blue, the financial sector is red and the utilities sector is green. Optimal bandwidths: investment grade (100,100,100); speculative grade (100,100,160).





appear to experience these effects earlier (from early 2003 compared to late 2003 for speculative grade issuers). Furthermore, the investment grade shows intensity fluctuations during 2000, when the speculative grade is relatively stable. This observation is in conflict with our intuition that speculative grade issuers have greater exposure to systemic risks (refer to credit rating definitions in appendix B), and the observation by Trück (2005) that speculative grade issuers are more sensitive than investment grade issuers are to systemic risks.

We do not discuss the differences between downgrade and upgrade intensities, since it solicits consideration of the causes of baseline intensity fluctuations. Therefore, we delay this discussion until migration intensities are controlled for market-driven covariates, where we have confidence that baseline intensity cyclicality is a result of systemic risks.

Demography-controlled models account for commonly cited and shown issuer-specific effects (for example, Lando and Skødeberg (2002) and Christensen et al. (2004)) before estimating a baseline intensity. Without including momentum and excitability, baseline intensity estimates can be distorted because the demography; the number of issuers that downgraded into the credit rating or the average time spent in the credit rating; can change over time. In addition to rejecting constancy, we can see that the baseline intensities of issuers suffer peaks and troughs that differ by industry sector.

5. market-reaction model

We use the market-reaction model to test the Standard & Poor's policy of rating corporate bonds through the cycle. Standard & Poor's undertake thorough quantitative and qualitative analyses on issuers to determine credit ratings, the components of which are unknown. As the introduction discusses, rating through the cycle implies that only persistent changes in the financial and business risks associated with an issuer affect their credit rating. That is, non-cyclical effects on the default risk affect downgrade and upgrade intensities. It is difficult, and possibly futile, to identify cyclical and persistent changes in an issuer's risk profile, as contributing factors would be numerous, highly correlated and *divisible*. For example, a rise in net income may be divided between improved management and a boom economy, or a stagnant net income may reflect improved management, but in a recession. Instead, we use the equity market evaluation of an issuer's financial and business risks relative to other issuers.

We represent the market reaction to a relative change in an issuer's risks by market-driven covariates. Firstly, we use the continuously compounded return in excess of the market index as representative of the risk profile of an issuer relative to other issuers, where a strengthening performance outlook relative to other issuers will cause a positive excess return. Equity markets provide us with this simple summary statistic (supposedly) based on analyses of risks. Bondholders do not have the same incentive for additional risk as equity-holders, however, with risky ventures by issuers not necessarily positive for bondholders. We fit also the volatility of the excess return to cater for this conflict of interests, allowing the bond riskiness to increase with any movement in equity. Lastly, we include the (natural logarithm of the) relative size of an issuer as measured by their market capitalisation because size affects the issuer's ability to service debt and to refinance. Both return and volatility measures are calculated over a three month period.

We diminish our sample size of issuers by approximately 58 percent when we merge debt and equity databases (see appendix A.2). The statistical significance of the coefficient estimates is convincing, and the economic significance is sensible (see appendix C.3), delivering insight into the relative impact of market-driven covariates for each credit rating. The power of these market-driven covariates to rank issuers according to relative risk is analogous to the market-reaction models applicability for examining rating through the cycle. Where we are not confident that the relative risk function is more informative than an assumption of population homogeneity (if Model Fits are not statistically significant improvements over the time-varying Markovian model), inference on the Breslow estimates for the baseline migration intensities is improper.

We obtain the Breslow estimates by setting $\hat{\boldsymbol{\beta}}_{id}$ in equation 6 as the coefficient estimates from partial likelihood estimation for each rating class. If $\hat{\boldsymbol{\beta}}_{id}$ captures the persistent financial and business risks, then the Breslow estimate produces the cumulative directional baseline migration intensity inclusive of cyclical financial and business risks, common effects and rating agency policy. Under Standard & Poor's policy of rating through the cycle, this Breslow estimate should be linear and the baseline intensity should be constant over time.

5.1. non-constancy of the market-reaction baseline intensities

We examine clumping of the baseline intensity estimates for rating classes in sequential half-years. We take a rejection of the null hypothesis; that the probability of being above the median is independent for each non-overlapping time increment; as analogous to a rejection of baseline intensity constancy and thus rating through the cycle. As in section 4.1, we present the median, positive deviations (n_+), positive groups (g_+) and p-value of the runs test. These results are shown in table 2 for downgrades, upgrades, each credit rating and each industry sector. We give little credence, and thus dedicate little discussion, to the runs tests where the relative risk function is unconvincing (Qualify? = N) or where a minority of increments contain d-migrations ($n_+ < 10$).

Despite controlling for persistent financial and business risks, the runs test confirms statistically significant clumping of positive deviations in many rating classes and industry sectors over the ten year period from 1 January 1997. In other words, issuers undergo intervals spanning at least one year of high or low baseline intensity over the decade.

The smaller sample size in comparison to the demography-controlled model diminishes our ability to make inference on baseline intensity constancy. Specifically, upgrade intensities from AA+ to A+ fail to provide strong enough relative risk functions to qualify for the runs test, nor do downgrade intensities from AA+ and AA-. Furthermore, too few migrations impair inference on financial sector downgrades from AA and B- to CCC, utilities sector downgrades from AA and BBB- to CCC, financial sector upgrades from BB to CCC and utilities sector upgrades from A, BBB+ and BB to CCC. Although unfortunate, it is difficult to conceive a statistical test for non-constancy that is able to provide for such small populations and control for issuer-specific effects.

Where the migrations are many and the Breslow estimate qualifies, the rejection of baseline intensity constancy is persuasive for downgrades. Particularly, all credit ratings in the industrial et al. sector have p-values less than ten percent, with all except industrial et al. AA rejecting the null hypotheses of constancy with ninety-five percent confidence. Of the financial sector; A+, BBB+ and BB fail to reject constancy; and of the utilities sector; only A+ fails to reject constancy. Overall, separating baseline downgrade intensities into half-yearly increments shows definitive clumping of deviations greater than (and less than) the median observation. The only rating grade where we do not observe clumping is when we are unable to make inference on the downgrade intensities for speculative grade utilities issuers.

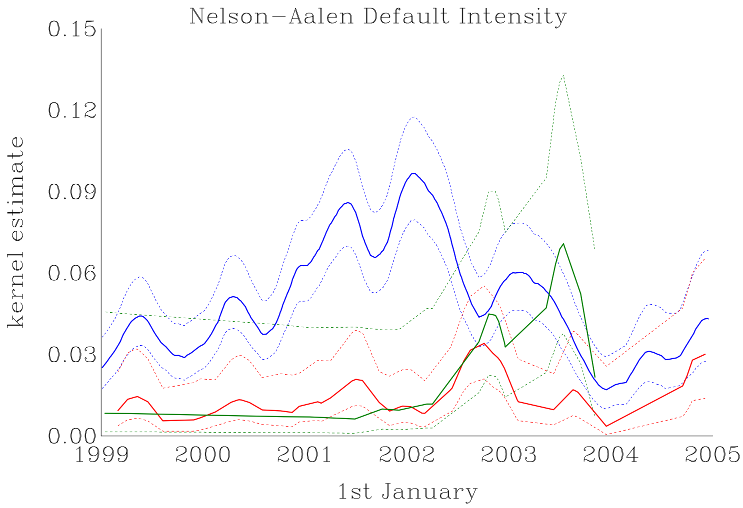
Table 2: Runs Test for the Market-Reaction Model in each credit rating (i) and industry sector from 1 January 1997 to 31 December 2006. Each test includes the median baseline intensity estimate integrated over half-year increments, the number of positive deviations (n_+), the number of positive groups (g_+), and the probability of observing no more than g_+ positive groups among n_+ positive deviations under an assumption of increment independence (p-value). *Qualify?* indicates the statistical significance of the relative risk Model Fit (Y=yes, N=no).

Industry Sector		Industrial et al.			Financials			Utilities		
Rating (i)	Qualify?	median	$n_+ - g_+$	p-value	median	$n_+ - g_+$	p-value	median	$n_+ - g_+$	p-value
The Downgrade Migrations										
AA+	N	0	4 − 3	0.239	0	3 − 3	1.000	0	3 − 3	1.000
AA	Y	0.005	10 − 6	0.081	0	7 − 6	0.643	0	3 − 3	1.000
AA-	N	0.039	10 − 6	0.081	0	9 − 5	0.033	0.021	10 − 4	0.001
A+	Y	0.016	10 − 5	0.013	0.007	10 − 7	0.285	0.002	10 − 6	0.081
A	Y	0.011	10 − 4	0.001	0.004	10 − 4	0.001	0.008	10 − 3	0.000
A-	Y	0.012	10 − 5	0.013	0.006	10 − 4	0.001	0.008	10 − 5	0.013
BBB+	Y	0.011	10 − 4	0.001	0.007	10 − 8	0.625	0.01	10 − 4	0.001
BBB	Y	0.014	10 − 5	0.013	0.007	10 − 2	0.000	0.005	10 − 3	0.000
BBB-	Y	0.001	10 − 3	0.000	0	10 − 5	0.013	0	8 − 5	0.084
BB+	Y	0.001	10 − 3	0.000	0.001	10 − 5	0.013	0	4 − 4	1.000
BB	Y	0.009	10 − 4	0.001	0.002	10 − 6	0.081	0	4 − 3	0.239
BB-	Y	0.013	10 − 3	0.000	0.006	10 − 3	0.000	0	4 − 4	1.000
B+	Y	0.005	10 − 2	0.000	0.004	10 − 5	0.013	0	6 − 3	0.011
B	Y	0.001	10 − 3	0.000	0.001	10 − 4	0.001	0	5 − 3	0.051
B-	Y	0	10 − 4	0.001	0	8 − 3	0.001	0	0 − 0	−
CCC+	Y	0.001	10 − 3	0.000	0	8 − 6	0.340	0	4 − 3	0.239
CCC	Y	0	10 − 5	0.013	0	2 − 1	0.043	0	2 − 2	1.000
The Upgrade Migrations										
AA+	N	0	0 − 0	−	0	0 − 0	−	0	0 − 0	−
AA	N	0	1 − 1	1.000	0	1 − 1	1.000	0	0 − 0	−
AA-	N	0	5 − 4	0.372	0	0 − 0	−	0	1 − 1	1.000
A+	N	0	5 − 4	0.372	0	8 − 4	0.011	0	4 − 2	0.016
A	Y	0.273	10 − 5	0.013	0.508	10 − 6	0.081	0	5 − 3	0.051
A-	Y	3.649	10 − 4	0.001	2.261	10 − 5	0.013	2.516	10 − 4	0.001
BBB+	Y	0.543	10 − 6	0.081	0.396	10 − 6	0.081	0	7 − 5	0.214
BBB	Y	0.326	10 − 7	0.285	0.226	10 − 6	0.081	0.168	10 − 6	0.081
BBB-	Y	0.72	10 − 4	0.001	0.539	10 − 7	0.285	0.925	10 − 6	0.081
BB+	Y	4.516	10 − 6	0.081	2.422	10 − 7	0.285	3.167	10 − 5	0.013
BB	Y	1.929	10 − 5	0.013	0	5 − 3	0.051	0	5 − 4	0.372
BB-	Y	11.719	10 − 3	0.000	0	7 − 4	0.035	0	6 − 3	0.011
B+	Y	3.162	10 − 7	0.285	0	5 − 4	0.372	0	5 − 3	0.051
B	Y	1.512	10 − 6	0.081	0	8 − 5	0.084	0	0 − 0	−
B-	Y	8.48	10 − 7	0.285	0	5 − 4	0.372	0	4 − 3	0.239
CCC+	Y	3.572	10 − 6	0.081	0	4 − 4	1.000	0	2 − 1	0.043
CCC	Y	2.402	10 − 6	0.081	0	2 − 2	1.000	0	0 − 0	−

The baseline downgrade intensity from AA- for the financial sector provides an example where the rejection of constancy is tempting for categories that do not qualify for inference. Despite only downgrades in nine of the twenty half-years, these half-years are clumped together and usually contain multiple downgrades—cyclicality is probably present. Regardless, we maintain our conservatism in conducting inference because these statistics could be a product of low populations if additional investigation was unavailable.

Upgrades in the industrial et al. sector demonstrate statistically significant clumping of positive deviations for credit ratings A, A-, BBB-, BB and BB-. Upgrades from A- in the financial sector and from A- and BB+ in the utilities sector reject constancy as well. Despite few rejections, many of the qualifying p-values are less than ten percent ($g^+ \leq 6$). Overall, clumping is evident in some credit ratings, but the degree of clumping is far less significant than in the downgrade intensities. Moreover, half of the investment grade credit ratings for all industry sectors and most of the speculative grade credit ratings for financial and utilities sector forbid inference due to inaccurate relative risk functions or few upgrades.

Figure 6: Smoothed Nelson-Aalen Default Intensity Estimates for each industry sector, rating grade and migration direction from 1 January 1999 to 31 December 2004. The industrial et al. sector is blue, the financial sector is red and the utilities sector is green. Optimal bandwidths: (100,160,100).



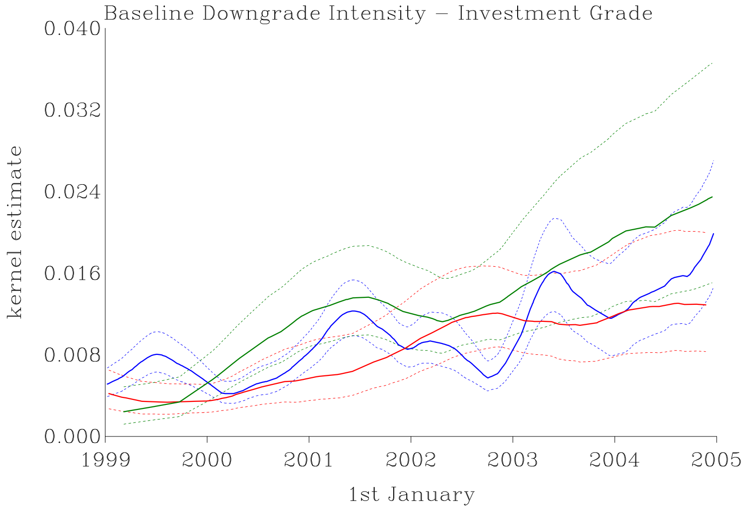
5.2. smoothed estimates of the market-reaction baseline intensities

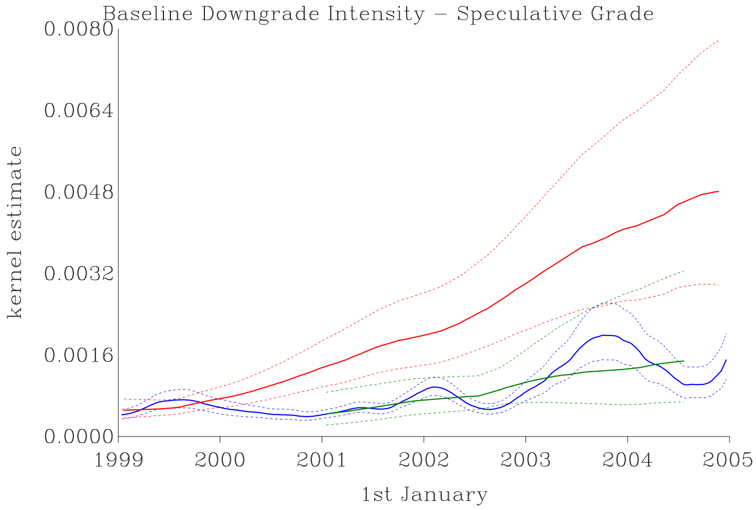
Smoothed estimates of the baseline intensities conclude the analysis. In this section, the baseline intensity estimates represent cyclical financial and business risks, risks common to all issuers in an industry sector and changes in Standard & Poor's policy. Baseline intensities should not reflect persistent changes in an issuer's financial and business risks. Under rating through the cycle, we expect the smoothed intensities estimates to be approximately constant.

Firstly, however, we propose a proxy for systemic risks present over the sample period: figure 6 shows smoothed Nelson-Aalen estimates (Andersen et al., 1993, section 4.1) of the default intensities for each industry sector regardless of credit rating. If Standard & Poor's base a rating assessment on long-term default intensities, fluctuations of these defaults intensities should not be indicative of credit rating migrations. We expect speculative grade issuers to be more reactive to heightened short-term default risks because they may not be long-term prospects, but investment grade issuers should be unmoved by short-term systemic risk fluctuations under a policy of rating through the cycle.

We adopt the aggregation technique of section 4.2, where we compile the Breslow estimates of all industry-stratified baseline intensities in a rating grade for an accurate picture of the behaviour of the these intensities. Recall, this aggregation reduces the graphics to representing the shape of the baseline intensities, fluctuating when common risks change. We do not find estimates of the magnitudes of the baseline intensities, since the average baseline intensity is different between credit ratings in the same rating grade. Also similar to section 4.2, the relative risk function must be a statistically significant improvement on a population-homogeneous model to qualify for inclusion in the aggregated smoothed estimate. For this reason, we exclude credit ratings AA+ and AA- from downgrade intensities and AA+ to A+ from upgrade intensities. The bandwidths of the smoothed estimates

Figure 7: Smoothed Baseline Downgrade Intensity Estimates for the Market-Reaction Model for each industry sector and rating grade from 1 January 1999 to 31 December 2004. The industrial et al. sector is blue, the financial sector is red and the utilities sector is green. Optimal bandwidths: investment grade (160,320,390); speculative grade (140,630,700).





are determined by minimising equation 9 to the nearest ten calendar days (subject to a minimum of 100 and a maximum of 700).

Figure 7 contains the smoothed estimates for downgrades from the investment and speculative grades between 1 January 1999 and 31 December 2004 . Confidence bands reflect the uncertainty, giving a range of ninety-five percent confidence around the smoothed estimates. These bands capture the variation in the Breslow estimate and the subsequent kernel estimates, although they assume that $\boldsymbol{\beta}_{id} = \hat{\boldsymbol{\beta}}_{id}$.

To appreciate the effects of bandwidth choice, notice the difference between the industrial et al. and financial sectors in the investment grade credit ratings, where the former has half the bandwidth of the latter (160 versus 320 calendar days). Fluctuations are more pronounced in the industrial et al. sector baseline intensity estimates whereas the financial sector is tame. Furthermore, the financial sector has a bandwidth of 630 calendar days in the speculative grade, with the smoothed estimate barely distinguishable from a linear estimate. We must balance the economic significance found with small bandwidths with the statistical significance found with large bandwidths. (We see that a third consideration—bias—is at play in the later upgrade intensities, where bandwidth optimisation imposes small bandwidths on sparse data to avoid bias in the smoothed estimate.)

The confidence bands for baseline downgrade intensities in the financial and utilities sectors are relatively wider in comparison to the industrial et al. sector than is the case with the demography-controlled model. Financial issuers contribute less to the experiments in the market-reaction model because public listing is rarer. Despite these wider confidence bands, constancy of the baseline intensities appears dubious in all industry sectors from the investment grade, and in the industrial et al. and financial sectors from the speculative grade. In addition, industry heterogeneity is again evident, with the behaviour of the smoothed estimates of different industries divergent on multiple occasions.

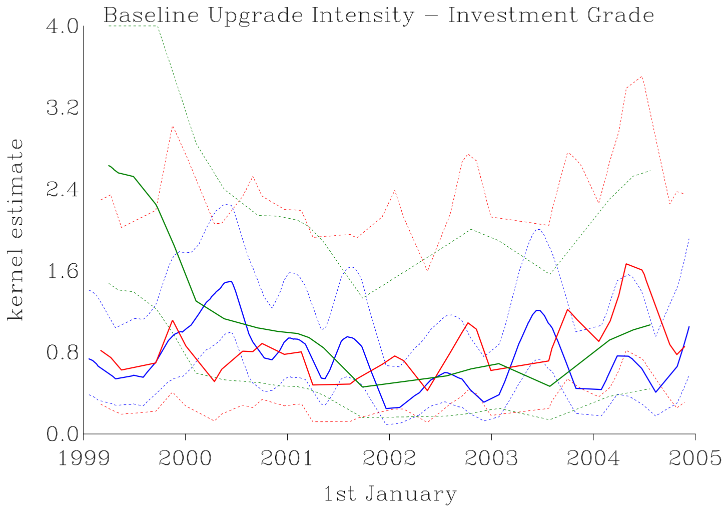
The common risks for industrial et al. issuers fluctuate over the sample period in both investment grade and speculative grade credit ratings. Fluctuations appear at similar locations to the demography-controlled model, although the market-driven covariates absorb the degree of some of the peaks. The baseline downgrade intensities rise in mid-1999 and over the period from mid-2001 to mid-2002—similar to the default intensity of figure 6. Unlike the default intensity, however, industrial et al. issuers suffer heightened baseline downgrade intensities from early 2003.

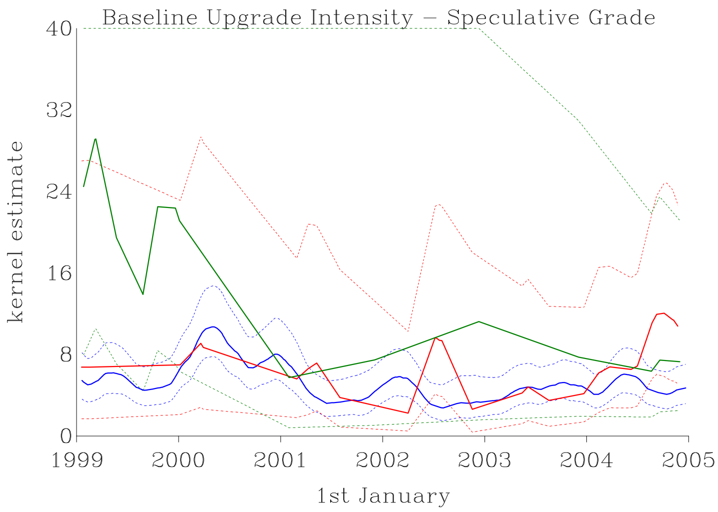
As mentioned, inference on financial issuers' baseline intensities is difficult because of smaller sample sizes. The baseline downgrade intensity increases over the sample period in both investment and speculative grade credit ratings. The heightened default risk follows shortly after the jump in common risks in mid-2002 for investment grade issuers. We remain weary, however, since this jump in baseline downgrade intensity persists for the remainder of the period, possibly indicting a Standard & Poor's policy change regarding investment grade financial issuers (although Amato and Furfine (2004) conclude that rating policy is constant over time).

We make no conclusion for speculative grade utilities issuers, and only passing comment on the investment grade utilities issuers—baseline intensities are not constant. Small samples make describing the behaviour of these issuers prone to errors, and the low default rates make the smooth Nelson-Aalen estimates uninformative. In fact, so few downgrades occur from utilities that we are unable to define the smoothed estimate prior to 2001.

Figure 8 shows the baseline upgrade intensities from the investment and speculative grades. The number of upgrades after introducing market-driven covariates makes inference on the baseline upgrade intensity for financial and utilities issuers impossible—we cannot reject a constant baseline intensity in these industry sectors for either rating grade. To support this, we can fit a horizontal line through each of these estimates without intercepting a confidence band.

Figure 8: Smoothed Baseline Upgrade Intensity Estimates for the Market-Reaction Model for each industry sector and rating grade from 1 January 1999 to 31 December 2004. The industrial et al. sector is blue, the financial sector is red and the utilities sector is green. Optimal bandwidths: investment grade (100,100,280); speculative grade (100,110,120).





The industrial et al. issuers' baseline upgrade intensity allows a more considered analysis. Both investment grade and speculative grade credit ratings experience a peak in upgrade intensities in early 2000, and a trough in upgrade intensities from late 2001 to early 2003. From 2004, however, investment grade issuers experience variable common risks, whereas speculative grade issuers remain relatively stable.

Data sparsity limits comparisons of the downgrade intensities and upgrade intensities in the financial and utilities sectors. The downgrade intensities for financial issuers appear to trend upwards over the period, whereas the upgrade intensities do not trend in either direction. The ebb in downgrade intensities in 2000 appears to correspond to the peak in upgrade intensities, although both baseline intensities are heightened in 2003. There is very little visual evidence to support the intuition that baseline upgrade intensities fluctuations negatively correlate to baseline downgrade intensities.

Overall, there is a strong argument that issuers in the industrial et al. sector experience cyclicality in their baseline migration intensities—for both downgrades and upgrades. Non-constancy of the baseline downgrade intensities has implications for the management of a portfolio of corporate bonds. Under a regime where the credit rating matters, an increase in the baseline downgrade intensities could cause the portfolio to fall below minimum quality requirements. Issuers in the same stratum share non-constant baseline intensities and thus issuers in a portfolio have correlation in credit rating migrations.

These concerns are particularly pertinent for banks and other institutions under the Basel II Capital Accord. Firstly, Basel II imposes capital provisions for credit risks, with the risk weightings for calculating minimum capital provisions increasing with debt riskiness (for example, a 20% risk weight for corporate debt rated between AAA and AA-, but a 150% risk weight for corporate debt with credit ratings below BB- (Basel, 2004, paragraph 66)). This compounds the potential expense of systemic risks, where a credit rating downgrade may cause a price drop (devaluing assets) as well as a need to expand capital provisions, since the risk weightings for calculating minimum capital provisions may increase. Secondly, banks can reduce their exposure to counterparty risks in calculating the provisions by accounting for collateral. The definition of eligible collateral, however, permits corporate debt of investment grade and not speculative grade (Basel, 2004, paragraph 145). Again, systemic risks of credit rating downgrades complicate the banks ability to forecast the eligibility of collateral. Furthermore, eligible collateral must not be “materially positively correlated” with the counterparty risk (Basel, 2004, paragraph 124), which is doubtful if strong systemic risks govern both capital requirements and collateral eligibility.

6. further research

The focus of this paper is on rating through the cycle, and although we examine cyclicality, we do not attempt to explain its causes. A regression of the baseline intensity may provide insight into the causes of cyclicality. Particularly, introducing indicators for industry business cycles and macroeconomic effects could deliver a better understanding of the baseline intensity and provide a means for forecasting migration intensities. Koopman and Lucas (2005) achieve this in modelling default rates, contending that business cycles and default rates are co-cyclical, which encourages investigations into whether this co-cyclicality extends to credit rating migration intensities. Although they also focus on default, Stefanescu et al.'s (2006) use Markov Chain Monte Carlo techniques to fit issuer-specific and macroeconomic covariates to examine systemic risks could prove fruitful in forecasting baseline intensities.

Under a strong assumption of cyclicality, where cycles are of predictable length and magnitude, we may use a combination of trigometric functions for modelling the baseline intensity. Although not as flexible as using common effect regressors that allow cycles of undefined length and magnitude, this approach may be favourable if we cannot rely on macroeconomic forecast data or we need the baseline intensity process to be perfectly predictable. This methods requires long periods of data for calibration—as found by Koopman et al. (2005) when using this approach in modelling default rates—which may be difficult if the merging of databases is needed. Regardless, fitting trigometric functions to the baseline intensities may provide a superior assumption to constant baseline intensities where we consider only the rating processes themselves—such as the demography-controlled model.

Given baseline intensity forecasts for all competing risks, it is possible to build a survival model. That is, one could find the probability of remaining in the same credit rating, defaulting, or remaining in a group of credit ratings (such as the investment grade credit ratings) over defined periods. This allows management of assets to assign probabilities of meeting debt quality targets. Furthermore, if rating through the cycle is fictional, banks need to establish correlated probabilities of breaching minimum credit quality to forecast compliance with Basel II.

7. conclusion

Standard & Poor's policy of rating through the cycle is an aspiration rather than a realisation. This has implications for asset management, where systemic risks can change the migration intensities of all issuers in a stratum. That is, the correlation between issuers' credit ratings complicates the probability of maintaining credit quality or survival targets of a debt portfolio into the future. Principally, Standard & Poor's unmet aspiration has serious reverberations for banks and their compliance with Basel II, since capital provisions and collateral eligibility are dependent on strict credit quality standards.

We adapt the runs test to the baseline component of the Evans' (2007) directional multiplicative intensity model. Subsequent increments of baseline intensity should be independent under baseline intensity constancy, which rating through the cycle implies. We are able to demonstrate that clumping occurs in all but the least populated credit ratings, meaning cyclicality of undefined length and size is present and we can reject baseline intensity constancy.

Initially, we apply a demography-controlled model, where momentum and excitability are fit to test non-constancy beyond these effects. We reject constancy in most credit ratings using the runs test and observe cyclicality in the baseline downgrade intensities using kernel estimates. While these results provide awareness of baseline intensity behaviour after controlling for demographic effects (the entry direction into a credit rating and the time spent in a credit rating), they fail to repudiate rating through the cycle policy because Standard & Poor's consider an issuer's non-cyclical financial and business risks. Moreover, smoothed baseline intensity estimates support previous evidence on the need for industry stratification.

We propose that an equity market's relative reaction to a change in an issuer's risks affords the best proxy to Standard & Poor's measure of a change in an issuer's persistent financial and business risks. Thus, we apply a market-reaction model, where excess return, volatility and relative market capitalisation are fit to test baseline intensity non-constancy and rating through the cycle policy. The most populous credit ratings and industry sectors reject baseline intensity constancy, finding statistically significant non-constancy in most baseline downgrade intensities from the industrial et al. and financial sectors. While cyclicality is present in baseline upgrade intensities as well, the results are both statistically and economically less convincing. Unfortunately, imprecise data merging techniques between the debt and equity databases diminishes the upgrades samples of financial and utilities issuers. Thus, inference on baseline intensities in the utilities sector using the runs test is minimal, and the upgrade baseline intensity estimates in the financial and utilities sectors remain unconvincing.

The directional multiplicative intensity model offers a flexible and impressive system for analysing migration intensities common to all issuers, where we model the baseline intensity after controlling for issuer-specific risks. While this paper dealt exclusively with the policy of rating through the cycle, this model provides scope for extensions into the causes and consequences of baseline intensity cyclicality. Furthermore, we implore researchers with access to precise debt and equity merging data to refine the pictorial evidence of cyclicality.

Appendices

A. data information

A.1. source data

FISD		
Field	Use in Analysis	Notes
Issuer Data		
issuer_id	identification	
issuer_cusip	merging sets	The primary identifier for merging databases
industry_group	industry identification	Industrial, financial, utilities, government, miscellaneous
industry_code	industry idenitification	Used to filter banks from financials
country_domicile	merging sets	Used to corroborate merging link
Static Issue Data		
issue_id	identification	
maturity	right-censoring times	Used for attaining issuer-specific ratings
rating_type	rating agency	Use only Standard & Poor's ratings
Dynamic Issue Data		
rating	credit rating	see appendix B
rating_date	credit rating migration dates	

CRSP		
Field	Use in Analysis	Notes
Static Data		
npermno	identification	
cusip	merging sets	The primary identifier for merging databases
linkdt	merging sets	Used to find where merging links correspond
linkenddt	merging sets	Used to find where merging links correspond
linktype	merging sets	Used to find where merging links correspond
Dynamic Data		
sasdate	date	
prc	size	
ret	return and volatility	
shrout	size	
shrsdt	size	
shrenddt	size	
Indices Data		
caldt	date	
vwretd	return and volatility	
totval	size	

A.2. data summary

Standard & Poor's credit rating summary statistics between 1 January 1997 and 31 December 2006 for each credit rating and industry sector. Demography-Controlled and Market-Reaction columns display the percent of downgrades and upgrade eligible for each model.

				Total Migrations		Demography-Controlled		Market-Reaction	
Rating	Industry	Issuers	Exposure	Downgrades	Upgrades	Downgrades	Upgrades	Downgrades	Upgrades
AAA	Industrial	73	386	41	0	10%	-	22%	-
	Financial	83	326	51	0	22%	-	2%	-
	Utilities	6	36	4	0	50%	-	25%	-
AA+	Industrial	27	150	30	15	37%	53%	13%	0%
	Financial	23	92	38	2	34%	50%	8%	0%
	Utilities	1	14	7	0	29%	-	43%	-
AA	Industrial	46	299	87	19	53%	42%	33%	5%
	Financial	71	231	67	8	51%	38%	10%	13%
	Utilities	6	48	16	0	25%	-	38%	-
AA-	Industrial	66	409	116	34	58%	59%	31%	15%
	Financial	103	450	131	23	40%	57%	12%	0%
	Utilities	17	185	55	4	53%	50%	35%	75%
A+	Industrial	127	701	192	31	63%	39%	31%	19%
	Financial	166	816	169	97	54%	63%	15%	13%
	Utilities	36	234	67	20	57%	55%	33%	30%
A	Industrial	148	994	234	80	55%	49%	40%	34%
	Financial	231	1170	187	180	51%	57%	11%	14%
	Utilities	43	324	90	23	61%	39%	31%	26%
A-	Industrial	170	867	259	93	71%	59%	46%	42%
	Financial	216	1108	145	209	48%	50%	20%	11%
	Utilities	62	479	131	35	52%	60%	24%	37%
BBB+	Industrial	224	1119	300	124	66%	70%	43%	38%
	Financial	217	968	159	186	58%	51%	16%	13%
	Utilities	94	412	136	40	62%	55%	17%	35%
BBB	Industrial	257	1499	325	204	68%	55%	45%	39%
	Financial	158	831	127	141	57%	44%	17%	17%
	Utilities	106	458	110	53	65%	45%	19%	21%
BBB-	Industrial	176	1174	314	217	70%	67%	43%	34%
	Financial	145	697	118	137	53%	40%	15%	22%
	Utilities	86	408	117	53	60%	62%	12%	32%
BB+	Industrial	164	802	226	186	81%	67%	43%	44%
	Financial	59	321	67	83	67%	52%	30%	22%
	Utilities	29	160	40	45	75%	82%	13%	33%
BB+	Industrial	118	623	201	124	75%	62%	40%	39%
	Financial	54	180	64	59	81%	59%	23%	12%
	Utilities	18	90	45	24	73%	79%	13%	29%
BB-	Industrial	193	902	289	170	61%	58%	38%	40%
	Financial	41	162	64	46	77%	52%	28%	20%
	Utilities	16	98	31	23	77%	78%	16%	35%
B+	Industrial	298	1511	422	214	55%	58%	38%	33%
	Financial	58	226	71	52	68%	56%	30%	13%
	Utilities	25	78	31	27	55%	67%	26%	22%
B	Industrial	427	2046	595	286	48%	40%	35%	41%
	Financial	37	150	66	46	76%	52%	39%	22%
	Utilities	29	55	31	22	87%	86%	23%	0%
B-	Industrial	500	2384	742	317	50%	38%	28%	34%
	Financial	39	169	52	30	71%	53%	25%	17%
	Utilities	16	39	12	26	83%	81%	0%	27%
CCC+	Industrial	262	769	478	111	87%	59%	30%	40%
	Financial	15	55	38	11	92%	73%	29%	36%
	Utilities	7	33	15	14	100%	86%	27%	21%
CCC	Industrial	176	384	321	80	92%	78%	31%	35%
	Financial	14	33	28	9	96%	89%	11%	22%
	Utilities	7	14	20	3	100%	100%	10%	0%
CCC-	Industrial	548	348	451	61	100%	92%	23%	28%
	Financial	60	49	54	6	96%	100%	13%	50%
	Utilities	27	21	20	11	100%	100%	10%	18%

B. rating definitions

Rating	Desciption
AAA	extremely strong capacity to meet its financial commitments
AA	very strong capacity to meet its financial commitments
A	strong capacity to meet its financial commitments but is somewhat more susceptible to the adverse effects of changes in circumstances and economic conditions than obligors in higher-rated categories
BBB	adequate capacity to meet its financial commitments. However, adverse economic conditions or changing circumstances are more likely to lead to a weakened capacity of the obligor to meet its financial commitments.
BB	faces major ongoing uncertainties and exposure to adverse business, financial, or economic conditions which could lead to the obligor's inadequate capacity to meet its financial commitments.
B	currently has the capacity to meet its financial commitments. Adverse business, financial, or economic conditions will likely impair the obligor's capacity or willingness to meet its financial commitments.
CCC	currently vulnerable, and is dependent upon favorable business, financial, and economic conditions to meet its financial commitments.
CC	currently highly vulnerable.
D, SD	default
NR	An issuer designated NR is not rated.
RS	regulatory supervision

source: www.standardandpoors.com

C. coefficient estimates

C.1. partial likelihood estimation

We express the partial likelihood function for the full migration intensity, $d\Lambda_{ij,k\ell}$, as

$$PL(\boldsymbol{\beta}_{id}) = \prod_{\ell}\prod_{k}\prod_{t>0}\left(\frac{Y_{i,k\ell}(s)\exp\left\{\boldsymbol{\beta}'_{id}\mathbf{X}_k(t)\right\}}{\sum_{k=1}^{m_\ell} Y_{i,k\ell}(s)\exp\left\{\boldsymbol{\beta}'_{id}\mathbf{X}_k(t)\right\}}\right)^{d\tilde{N}_{id,k\ell}(s)},$$

where the time-related product ($\prod_{t>0}$) is a product integral (Andersen et al., 1993). For estimation, we take the natural logarithm,

$$l(\boldsymbol{\beta}_{id}) = \sum_{\ell}\sum_{k}\int_0^t \left(Y_{i,k\ell}(s)\boldsymbol{\beta}'_{id}\mathbf{X}_k(t) - log\left(\sum_{k=1}^{m_\ell} Y_{i,k\ell}(s)e^{\boldsymbol{\beta}'_{id}\mathbf{X}_k(t)}\right)\right) d\tilde{N}_{id,k\ell}(s). \quad (11)$$

To estimate $\boldsymbol{\beta}_{id}$, we find the score vector and information matrix by differentiating equation 11 once and twice respectively,

$$\begin{aligned}
\mathcal{U}\left(\boldsymbol{\beta}_{id}, t\right) &= \sum_{\ell}\left(\sum_{k=1}^{m_\ell}\int_0^t \mathbf{X}_k(s)d\tilde{N}_{id,k\ell}(s) - \int_0^t \mathcal{E}\left(\boldsymbol{\beta}_{id}, s\right)d\tilde{N}_{id,\cdot\ell}(s)\right) \text{ and} \\
\mathcal{I}\left(\boldsymbol{\beta}_{id}, t\right) &= -\sum_{\ell}\int_0^t \mathcal{V}\left(\boldsymbol{\beta}_{id}, s\right)d\tilde{N}_{id,\cdot\ell}(s),
\end{aligned}$$

where,

$$\begin{aligned}
\mathcal{E}\left(\boldsymbol{\beta}_{id}, t\right) &= \frac{\sum_{k=1}^{m_\ell}\mathbf{X}_k(t)Y_{i,k\ell}(s)\exp\left\{\boldsymbol{\beta}'_{id}\mathbf{X}_k(t)\right\}}{\sum_{k=1}^{m_\ell} Y_{i,k\ell}(s)\exp\left\{\boldsymbol{\beta}'_{id}\mathbf{X}_k(t)\right\}}, \\
\mathcal{V}\left(\boldsymbol{\beta}_{id}, t\right) &= \frac{\sum_{k=1}^{m_\ell}\mathbf{X}_k(t)^{\otimes 2}Y_{i,k\ell}(s)\exp\left\{\boldsymbol{\beta}'_{id}\mathbf{X}_k(t)\right\}}{\sum_{k=1}^{m_\ell} Y_{i,k\ell}(s)\exp\left\{\boldsymbol{\beta}'_{id}\mathbf{X}_k(t)\right\}} - \mathcal{E}\left(\boldsymbol{\beta}_{id}, t\right)^{\otimes 2}, \text{ and} \\
\tilde{N}_{id,\cdot\ell}(t) &= \sum_{k=1}^{m_\ell}\tilde{N}_{id,k\ell}(t).
\end{aligned}$$

The estimate for $\boldsymbol{\beta}_{id}$, $\hat{\boldsymbol{\beta}}_{id}$, is found by evaluating the score vector at zero, $\mathcal{U}(\boldsymbol{\beta}_{id}, \tau) = 0$. The standard error and covariance associated with $\hat{\boldsymbol{\beta}}_{id}$ are approximated by the inverse of the observed information matrix, which we use for estimating the statistical significance of the coefficient estimates (Therneau and Grambsch, 2000, chap. 3).

In addition, we measure the performance of a model overall by considering Model Fit statistics. We calculate Model Fit statistics as $-2\times l(\hat{\boldsymbol{\beta}}_{id})$, and we use these for comparisons between models fit on the same sample (smaller Model Fits statistics are preferable). Specifically, the Model Fit statistic for the time-varying Markovian model (the null model) is $-2 \times l(\mathbf{0})$, and the difference in these Model Fit statistics $(2(l(\hat{\boldsymbol{\beta}}_{id}) - l(\mathbf{0}))$, under a null hypothesis of $\boldsymbol{\beta}_{id} = \mathbf{0}$, follows a χ^2-distributed with degrees of freedom equal to the number of elements in $\mathbf{X}_k$. We demonstrate the improvement of the directional multiplicative intensity model over the time-varying Markovian model by citing these Model Fit statistics.

C.2. demography-controlled relative risk functions

Industry-Stratified Directional Migration Models with Momentum and Excitability Covariates. Coefficient estimates, $\hat{\beta}$, are accompanied by asterisks representing statistical significance: * is ninety percent, ** is ninety-five percent, and *** is ninety-nine percent. The Model Fit statistics ($-2\times$log-likelihood) are accompanied by asterisks representing the improvement over the null model.

Rating (i)	#From	#To	$\hat{\beta}_{id}^{momentum}$	$\hat{\beta}_{id}^{excite}$	Model Fit
The Downgrade Migrations					
AA+	41	26	0.794	−0.568	54**
AA	129	84	0.617**	−0.213**	320***
AA-	239	148	0.564***	0.535***	746***
A+	402	249	0.261*	−0.167***	1560***
A	513	280	0.640***	−0.198***	1932***
A-	573	321	0.802***	−0.127**	2229***
BBB+	655	373	1.000***	−0.124**	2612***
BBB	676	364	0.614***	−0.313***	2692***
BBB-	658	353	0.783***	−0.343***	2409***
BB+	519	258	1.386***	−0.302***	1607***
BB	403	236	0.823***	−0.442***	1251***
BB-	459	244	0.621***	−0.357***	1492***
B+	562	295	0.827***	−0.367***	2003***
B	625	347	0.896***	−0.294***	2430***
B-	692	401	0.637***	−0.288***	3019***
CCC+	622	398	0.415*	−0.298***	2885***
CCC	459	286	0.482	−0.275***	1707***
The Upgrade Migrations					
AA+	41	9	18.053	−0.062	19**
AA	129	11	2.025**	−0.291	44**
AA-	239	35	0.599	0.156	179
A+	402	84	0.412*	−0.274***	499***
A	513	150	0.355*	0.280**	1034***
A-	573	180	0.282*	0.045	1168
BBB+	655	203	0.482***	−0.085	1373***
BBB	676	199	0.417***	−0.021	1454**
BBB-	658	233	0.594***	0.048	1617***
BB+	519	204	0.414***	0.019	1269**
BB	403	131	0.567***	−0.134	642***
BB-	459	141	0.765***	−0.021	866***
B+	562	172	0.199	0.109	1164
B	625	158	0.409**	0.101	1035**
B-	692	157	0.907***	0.101	1108***
CCC+	622	86	1.018***	0.195	556**
CCC	459	73	1.148***	0.432	425**

C.3. market-reaction relative risk functions

Industry-Stratified Directional Migration Models with Return, Volatility and Size Covariates. Coefficient estimates, $\hat{\beta}$, are accompanied by asterisks representing statistical significance: * is ninety percent, ** is ninety-five percent, and *** is ninety-nine percent. The Model Fit statistics ($-2\times$log-likelihood) are accompanied by asterisks representing the improvement over the null model.

Rating (i)	#From	# To	$\hat{\beta}_{id}^{return}$	$\hat{\beta}_{id}^{volatility}$	$\hat{\beta}_{id}^{size}$	Model Fit
The Downgrade Migrations						
AA+	10	10	-34.595	274.642	1.890	6^{*}
AA	51	42	0.961	48.507	-0.298^{***}	158^{***}
AA-	93	71	-0.030	31.625^{**}	-0.079	329^{*}
A+	156	108	-1.332^{*}	76.435^{***}	-0.062	555^{***}
A	242	143	-1.525^{**}	39.464^{***}	-0.186^{***}	903^{***}
A-	284	180	-0.950^{**}	19.582^{***}	-0.227^{***}	1183^{***}
BBB+	298	178	-1.864^{***}	36.362^{***}	-0.157^{***}	1165^{***}
BBB	346	187	-2.300^{***}	30.404^{***}	-0.135^{***}	1324^{***}
BBB-	326	166	-1.146^{***}	59.055^{***}	-0.296^{***}	1054^{***}
BB+	263	122	-1.917^{***}	35.389^{***}	-0.356^{***}	701^{***}
BB	185	102	-1.738^{***}	40.203^{***}	-0.153^{*}	498^{***}
BB-	257	133	-1.160^{***}	32.924^{***}	-0.114^{*}	785^{***}
B+	332	187	-1.091^{***}	36.221^{***}	-0.167^{***}	1278^{***}
B	421	233	-1.741^{***}	32.166^{***}	-0.329^{***}	1571^{***}
B-	395	216	-1.521^{***}	37.702^{***}	-0.371^{***}	1444^{***}
CCC+	232	146	-1.574^{***}	43.733^{***}	-0.281^{***}	733^{***}
CCC	147	94	-1.743^{***}	42.990^{***}	-0.464^{***}	396^{***}
The Upgrade Migrations						
AA+	10	0	–	–	–	–
AA	51	2	4.376	-59.908	0.701	6
AA-	93	8	-1.922	49.712	0.969^{**}	31^{*}
A+	156	25	0.334	5.478	0.291	117
A	242	59	-0.105	16.261	0.383^{***}	369^{***}
A-	284	74	1.361	-24.397	0.489^{***}	451^{***}
BBB+	298	86	0.262	-32.057	0.250^{***}	529^{***}
BBB	346	114	2.223^{***}	7.216	0.224^{***}	815^{***}
BBB-	326	120	0.861	-12.417	0.259^{***}	805^{***}
BB+	263	115	1.551^{**}	-47.063^{***}	0.308^{***}	662^{***}
BB	185	61	0.845	-21.889	0.275^{**}	304^{**}
BB-	257	85	1.223^{*}	-80.372^{***}	0.314^{***}	474^{***}
B+	332	83	0.420	-22.932^{*}	0.356^{***}	590^{***}
B	421	127	1.681^{***}	-27.421^{***}	0.218^{***}	991^{***}
B-	395	118	1.306^{***}	-29.279^{***}	0.363^{***}	829^{***}
CCC+	232	49	0.836	-8.359	0.336^{***}	255^{***}
CCC	147	30	1.527^{**}	-23.301	0.185	124^{***}

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