

A Credit Risk Application of Multivariate Ordinal Regression Models using the R package mvord

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- ▶ Introduction and motivation
- ▶ Overview R package **mvord**
- ▶ Examples

- ▶ **Credit risk** is the risk of a loss arising from a failure (or default) of a counterparty to meet its contractual obligations (e.g., McNeil et al., 2015).
- ▶ **Credit ratings** are forward-looking opinions about the creditworthiness of an obligor.
- ▶ Credit ratings are **ordinal** assessments of credit risk and are primarily relevant for:
 - ▶ **investors**
 - ▶ **regulators** and **legislators**
 - ▶ **issuers**
 - ▶ **financial institutions**
- ▶ Credit ratings as well as (internally) estimated probabilities of default (PDs) are central measures of credit risk.

- ▶ Two modeling approaches:
 - **Credit rating models** (e.g., Blume et al., 1998; Alp, 2013; Baghai et al., 2014)
 - **Failure prediction models** (e.g., Shumway, 2001; Tian et al., 2015)
- ▶ **Correlated** ordinal data
 - Multiple correlated ratings assigned by different raters to one firm at the same point in time.
 - For each rater, there is serial dependence over the years.
- ▶ There is need for a **flexible model class** that can handle correlated ordinal and binary data:
 1. Heterogeneity in the rating methodology
 2. Heterogeneity in the covariates
 3. Unbalanced panel of firms

- ▶ i denotes the subject index (firm).
- ▶ j denotes the multiple measurement index (rater).
- ▶ $\mathbf{Y}_i = [Y_{ij}]_{j \in \{1, \dots, q\}}$ is a $(q \times 1)$ vector of **correlated** ordinal response variables which is observed together with covariates.
- ▶ The association between the \mathbf{Y}_i 's is captured by a multivariate structure imposed on the latent variables $\tilde{\mathbf{Y}}_i$:

$$\tilde{Y}_{ij} = \beta_{0j} + \mathbf{x}_{ij}^\top \boldsymbol{\beta}_j + \epsilon_{ij}, \quad \boldsymbol{\epsilon}_i = [\epsilon_{ij}]_{j \in \{1, \dots, q\}} \sim F_{i,q}(\mathbf{0}, \boldsymbol{\Sigma}_i),$$

where $F_{i,q}$ denotes the q -dimensional joint distribution of the errors $\boldsymbol{\epsilon}_i$.

- ▶ For each j ,

$$Y_{ij} = r \Leftrightarrow \theta_{j,r-1} < \tilde{Y}_{ij} \leq \theta_{j,r}, \quad r \in \{1, \dots, K_j\},$$

where $-\infty = \theta_{j,0} < \theta_{j,1} < \dots < \theta_{j,K_j-1} < \theta_{j,K_j} = \infty$ are response specific thresholds.

- ▶ The R package **mvord** (Hirk et al., 2018) implements pairwise likelihood estimation in the class of multivariate ordinal regression models in a flexible framework.
- ▶ Several identifiability constraints are supported.
- ▶ Multivariate probit and logit links are implemented.
- ▶ The correlation between the variables is accounted for by different (covariate dependent) error structures:
 - ▶ `cor_general()`: $\text{corr}(\epsilon_{ik}, \epsilon_{il}) = \rho_{ikl}$,
 - ▶ `cor_equi()`: $\text{corr}(\epsilon_{ik}, \epsilon_{il}) = \rho_i$,
 - ▶ `cor_ar1()`: $\text{corr}(\epsilon_{ik}, \epsilon_{il}) = \rho_i^{|l-k|}$.
- ▶ Constraints on the threshold and coefficient parameters can be set.
- ▶ Category-specific coefficients are supported.

- ▶ **Long-term issuer credit ratings** assigned by S&P, Moody's and Fitch for US companies excluding the financial and utilities sectors;
 - ▶ S&P: AAA, AA, A, BBB, BB, B, CCC, CC
 - ▶ Fitch: AAA, AA, A, BBB, BB, B, CCC, CC, C
 - ▶ Moody's: Aaa, Aa, A, Baa, Ba, B, Caa, Ca
 - ▶ Sources: Compustat North America[©] Ratings File, Moody's Default & Recovery Database[©], Fitch Rating Services.

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- ▶ **Failure indicator:** binary indicator set to one on occurrence of bankruptcy filing under Chapter 7 or Chapter 11, or default rating by CRAs in the one year-window following the rating observation;
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- ▶ **Covariates:** financial ratios and market variables;
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 - ▶ Sources: Compustat North America[©] Fundamentals Annual File, The Center for Research in Security Prices (CRSP).
- ▶ Period: 1999–2013

Model formula

```
> formula <- MMO2(SCR, Fitch) ~ 0 + R3 + R12 + R18 + R20 + R23 + R34 + R35 +  
+ RSIZE + BETA + SIGMA + MB + fyear
```

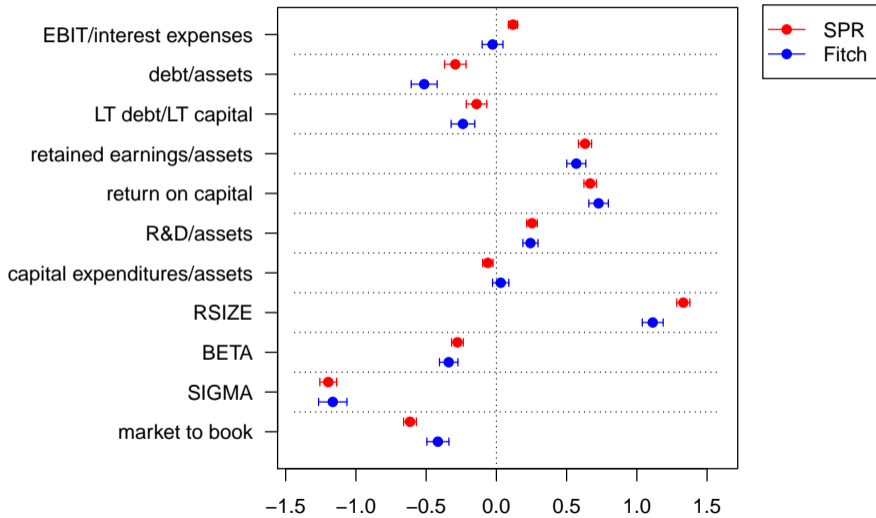
Constraints on thresholds

```
> threshold.constraints <- c(1, 1)
```

Function call

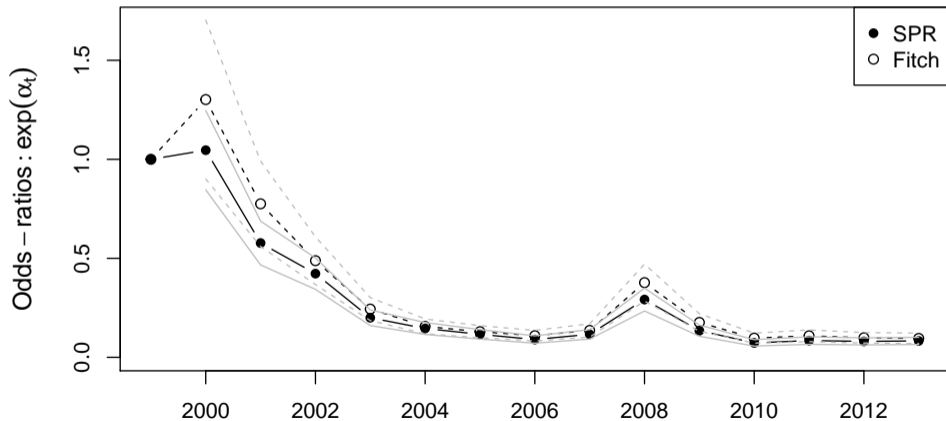
```
> res_SPR_Fitch <- mvord(formula,  
+ data = data_ordinal,  
+ threshold.constraints = c(1, 1),  
+ link = mvlogit(),  
+ error.structure = cor_general(~1))
```

A first simple example - Standardized regression coefficients



A first simple example - Year intercepts

$$\exp(\alpha_t) = \frac{\mathbb{P}(Y_{t,j} > r) / \mathbb{P}(Y_{t,j} \leq r)}{\mathbb{P}(Y_{1999,j} > r) / \mathbb{P}(Y_{1999,j} \leq r)}, \quad j \in \{\text{S\&P, Fitch}\}$$



Model formula

```
> formula <- MMO2(SPR, Moodys, Fitch) ~ 0 + R3 + R7 + R12 + R18 + R20 + R23 + R24 +  
+ R34 + R35 + RSIZE + BETA + SIGMA + MB
```

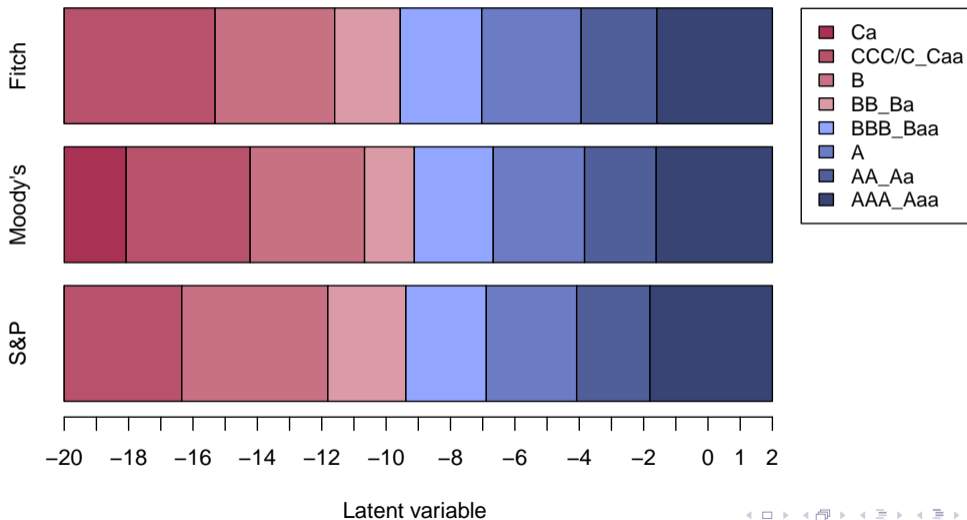
Constraints on regression coefficients

```
> coef.constraints <- c(1, 1, 1)
```

Function call

```
> res_SPR_Moodys_Fitch <- mvord(formula,  
+ data = data_ordinal,  
+ coef.constraints = c(1, 1, 1),  
+ link = mvlogit(),  
+ error.structure = cor_general(~1))
```

A joint model of credit ratings - Threshold coefficients



- ▶ We assume that S&P (S), Moody's (M) and Fitch (F) provide ratings on an ordinal scale based on a latent process:

$$\tilde{S}_i = \mathbf{x}_i^\top \boldsymbol{\beta}_S + \epsilon_{i,S},$$

$$\tilde{M}_i = \mathbf{x}_i^\top \boldsymbol{\beta}_M + \epsilon_{i,M},$$

$$\tilde{F}_i = \mathbf{x}_i^\top \boldsymbol{\beta}_F + \epsilon_{i,F},$$

where $\boldsymbol{\beta}_S$, $\boldsymbol{\beta}_M$ and $\boldsymbol{\beta}_F$ are vectors of coefficients and $\epsilon_{i,\cdot}$ are error terms .

- ▶ For a binary default or failure indicator (labeled by D) we assume:

$$\tilde{D}_i = \mathbf{x}_i^\top \boldsymbol{\beta}_D + \epsilon_{i,D},$$

where $\epsilon_{i,D}$ is a failure indicator specific error term.

- ▶ For the errors we assume $[\epsilon_{ij}]_{j \in \{S, M, F, D\}} \sim F_{i, q_i}(0, \mathbf{R}_i)$.

Model formula

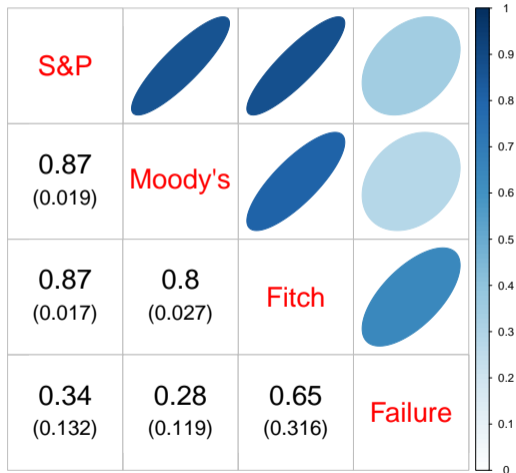
```
> formula <- MMO2(SPR, Moodys, Fitch, failInd) ~ 0 + R20 + R23 + R34 + SIGMA +  
+ BETA + R1 + R13 + R18 + 1AT + MB + R1d + R5 + R17M + R22M + R27a + R29 + R35a
```

Constraints on coefficients

```
> coef.constraints <- cbind(c(1,2,3,NA), c(1,2,3,NA), c(1,2,3,NA), c(1,2,3,4),  
+ c(1,2,3,NA), c(1,2,3,NA), c(1,2,3,NA), c(1,2,3,NA), c(1,2,3,4), c(1,2,3,NA),  
+ c(NA,NA,NA,1), c(NA,NA,NA,1), c(NA,NA,NA,1), c(NA,NA,NA,1), c(NA,NA,NA,1),  
+ c(NA,NA,NA,1), c(NA,NA,NA,1))
```

Function call

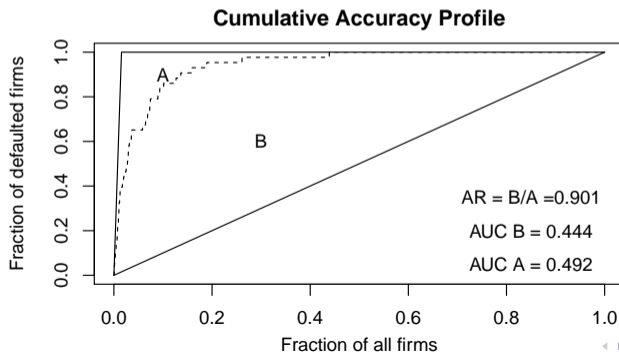
```
> res_joint <- mvord(formula, data = data_ordinal, link = mvlogit(),  
+ weights = "weights3raters", coef.constraints = coef.constraints,  
+ error.structure = cor_general(~1))
```



The proposed model allows to predict PDs conditional on the observed ratings from the CRAs:

$$\mathbb{P}(D_i = 1 | S_i = r_{iS}, M_i = r_{iM}, F_i = r_{iF}) = \frac{\mathbb{P}(D_i = 1, S_i = r_{iS}, M_i = r_{iM}, F_i = r_{iF})}{\mathbb{P}(S_i = r_{iS}, M_i = r_{iM}, F_i = r_{iF})},$$

where S_i , M_i and F_i denote the rating observations and D_i is the default indicator.



- ▶ The underlying latent process of the proposed model is assumed to have the following form:

$$\tilde{Y}_{it} = \mathbf{x}_{it}^{\top} \boldsymbol{\beta}_t + \epsilon_{it},$$

where

- $\boldsymbol{\beta}_t$ is a time-specific regression coefficient,
- ϵ_{it} is an error term with with autocorrelation structure of order one (AR(1)):

$$\begin{aligned}\epsilon_{it} &= \rho \epsilon_{i(t-1)} + \sqrt{1 - \rho^2} \eta_{it}, \\ \eta_{it} &\sim \mathcal{N}(0, 1).\end{aligned}$$

Model formula

```
> formula <- MMO(SPR, gvkey, fyear) ~ 0 + R3 + R9 + R12 + R18 + R20 + R23 +  
+ R24 + R34 + R35 + RSIZE + BETA + SIGMA + MB
```

Threshold constraints

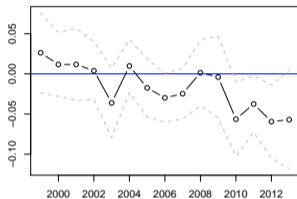
```
> threshold.constraints <- rep(1, nlevels(data_ordinal$fyear))
```

Function call

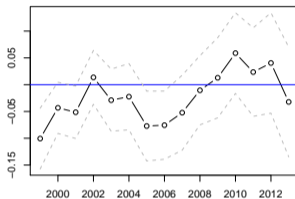
```
> res_ar1 <- mvord(formula, data = data_ordinal, link = mvprobit(),  
+ weights = "weights_SPR", threshold.constraints = threshold.constraints,  
+ error.structure = cor_ar1(~1))
```

Time varying coefficients (I)

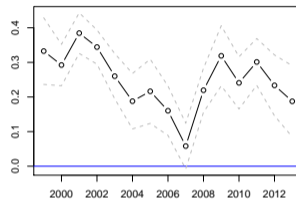
EBIT/interest expenses



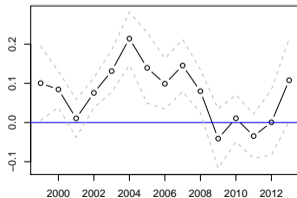
net PPE/assets



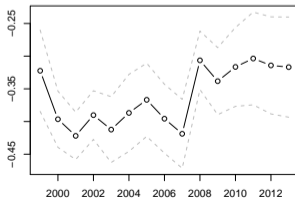
debt/assets



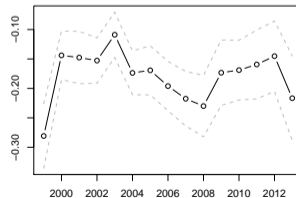
long term debt/long term capital



retained earnings/assets

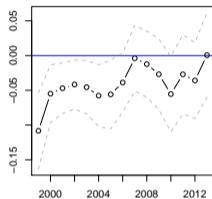


return on capital

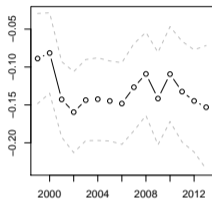


Time varying coefficients (II)

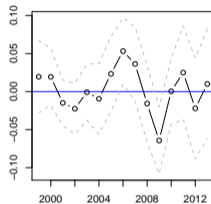
EBITDA/sales



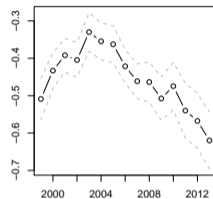
R&D/assets



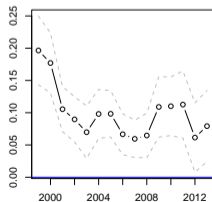
capital expenditures/assets



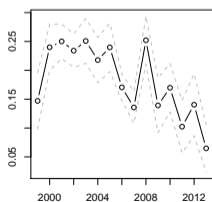
RSIZE



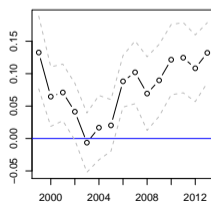
BETA



SIGMA



market to book



The R package **mvord** can be used to:

- ▶ create multivariate shadow ratings,
- ▶ gain insights into the rating behavior,
- ▶ investigate the heterogeneity among CRAs,
- ▶ measure association between ratings and failures,
- ▶ build a joint model of failures and credit ratings which allows to perform inference about the relationship between these outcomes,
- ▶ provide interesting insights from the joint distribution, i.e., conditional probabilities can be computed.

- ▶ Flexible modeling framework for multivariate ordinal regression models with:
 - outcome-specific threshold coefficients,
 - outcome-specific regression coefficients,
 - constraints on threshold and regression parameters,
 - different error structures and
 - two multivariate link functions.
- ▶ Package **mvord** is available on CRAN (Version 0.3.0).
- ▶ A comprehensive package vignette is available.
- ▶ Code snippets are available on <https://github.com/rhirk/RFinance2018>.

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Thank you for your attention!

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