Final Assignment: Predicting Director Compensation

Jasper Ginn (s6100848)

April 8, 2019

Introduction

$$\log(\widehat{\text{compensation}}_i) = \beta_0 + \beta_1 \text{age}_i + \beta_2 \text{male}_i + \beta_3 \text{SectorServices}_i + \beta_4 \text{SectorBasicMaterials}_i + \epsilon_i \quad (1)$$

From the PPC plots, we see that the data are violating the assumption of independence as the MAP of the correlation coefficient for the observed data indicates a strong positive correlation ($\hat{r}_{\text{MAP, PPC}} = .466$).

From figure XX and the posterior predictive checks, we observe that the data are not independent. That is, directors who are in the same board tend to are more similar to each other than directors from other boards. This is not unexpected: the data are hierarchical in nature such that individuals are nested in boards. Indeed, the results of the random effects model shows that the intra-class correlation coefficient ρ equals 57%, meaning that the expected correlation of two randomly picked directors from the same company is $\hat{r} = .573$.[1]

The final random effects model is presented in table YY. This model corresponds to the following equation.

$$\text{compensation}_{ij} = \gamma_{00} + u_{0j} + \gamma_{10} \cdot \text{Age}_{ij} + e_{ij}$$

Where γ_{00} is the overall intercept and u_{0j} is a company-specific error term. Notice that the fit of this model is much better than that of the previous models, indicating that the multilevel approach seems appropriate.

Given that the variable age only explains some 1.3% of the variance on level 1 and .8% of the variance on level 2, the conclusion is that we do not have the right predictors

Table 1: Model results

	Dependent variable:		
	Compensation		
	(1)	(2)	(3)
Constant	4.991 (4.936, 5.046)	4.821 (4.732, 4.910)	4.991 (4.877, 5.110)
SectorBasic Materials		.225 (.079, .370)	
SectorServices		.292 (.169, .414)	
Male	.065 (−.085, .215)	.153 (.095, .209)	
Age	.008 (0.000, .017)	.009 (.001, .017)	0.001 (.0035, .0155)
Intercept variance			.3392
Observations	336	336	336
Companies			52
Par.	4	6	47
DIC	508	488	289
R^2	.021	.098	
Residual Std. Error	.516	.501	.3423
Note:			Baseline is sector 'Financials'

[1] The results of running all different stages of a multilevel model are presented in another document.

Differences in Bayesian and Frequentist inference

The effect of changing the prior variance can be summarized using a posterior shrinking factor (CITE BETANCOURT) and posterior z-score. The shrinking factor shows us the factor by which the variance of the posterior distribution shrinks or expands compared to the prior variance. The posterior z-score tells us the direction and magnitude by which the posterior mean shifts compared to the prior mean; if we are confident in the precision of our domain knowledge (resulting in small prior variance), the resulting posterior weights this information strongly and we end up with a posterior mean that lies closer to the prior mean (represented by the z-score). However, given that we have small variance, and if this is not corroborated by the data, then the shrinkage factor will be large.

Other material

References

Lynch, S. M. (2007). Introduction to applied Bayesian statistics and estimation for social scientists. Springer Science & Business Media. Chapter 9.2

Aarts, E. (2019). Introduction to multilevel analysis and the basic two-level regression model, week 1 notes [powerpoint presentation]. *Introduction to Multilevel Analysis*, Utrecht University.