Toulouse School of Economics

Statistical Consulting: Adamantia-TSE

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Outline

I.Introduction

Introduction

- Adamantia - management consulting for banks
- Banks - financial intermediary
  - give out loans
- What if the loan creditor defaults?
  - Banks don't loan to those they think will default
- **Credit risk modelling** - use relevant financial indicators to assess probability of default
- Our premise: environmental variables need to be considered

Motivation: Climate Research

- IPCC: estimates 1.0 $^\circ$ C in global temperatures due to human activities (pre-industrial levels to now)
  - global warming is likely to reach 1.5 $^\circ$ C between 2030 and 2052
- Effects: extreme temperatures, heavy precipitation, droughts, rising sea levels...
  - Risks to physical capital
    - ★ regional crops become unsustainable
    - ★ trade infrastructure (ports, airport) destroyed
  - Costs due to transition
    - ★ heavy fines for carbon emission
    - ★ loss in demand for non-green firms
    - ★ costs for firms to adapt to new energy models

Motivation: Existing Models

- Climate risk modelling - data and methods are closely protected.
- Step 1: Build a new risk model
  - Adamantia's model was not available to us
- Step 2: incorporate climate risk
  - Variables not yet collected
  - Solution: develop an application which could incorporate potential variable after collection.

II.Literature Review

Literature Review: Types of Risk

- 3 Types of Risk:
  - Physical risks
    - ★ lower productivity
    - ★ decrease cash flows
    - ★ harm physical assets
  - Transition risks
    - ★ affect assets values
  - Liabilities
    - ★ costs related to non-green industry penalizations by government
- Two solutions:
  - Economic Policy - move credit in a way which softens transition costs
  - Changing capital requirements for banks
    - ★ this approach is more relevant for our project

Literature Review: Response to Risks

- There are several perspectives when considering the risk approach
  - Green Supporting Factor (GSF)
  - Brown Penalising Factor (BPF)
  - Environmental Risk Weighted Asset (combination of both)

Literature Review: Example

- Transition Score developed by Credit Agricole
  - Energy Transition Score provided by Vigeo (no greater details available)
  - Intended Nationally Determined Contribution for the asset's sector and geographic location, normalized for the specific year
- More information is very hard to find!

III.Data

Overview

- Data collected by a bank with the financial and qualitative rating of customers
- Contains financial indicators as covariates

	...1	ID	Status	Sectorofactivity	Financialrating	Qualitativerating
1	1	s1220365003572	SA	741J	10.88	4.55
2	2	s1226070978749	SAS	524Z	7.68	17.58
3	3	s1215871249328	SAS	513W	11.01	12.60
4	4	s1228387154387	-	911C	4.55	13.42
5	5	s1231436521553	SAS	524C	11.40	15.45
6	6	s1226655818815	SAS	514Q	8.65	12.12

	Qualitativeratingabouttransparency	Qualitativeratingaboutshareholderscontribution	Favorableeconomicmarket
1	9	3	0
2	17	5	15
3	17	12	8
4	15	6	15
5	17	5	15
6	14	5	12

	Sectorwillincrease	Managementquality	HoldbyabiggerFirm	CEOinvolved	Helpfromthegrouponlegal	Assets	Liability
1	0	3	1	1	0	30663333	30660333
2	7	20	0	1	1	1713000	1713000
3	3	9	0	0	0	2164000	2161000
4	5	13	0	0	0	0	0
5	5	14	1	1	0	79835000	79835000
6	5	9	1	1	0	55000	54000

Figure 1: Snapshot of the data

Variables of interest

- Financial Rating
  - Turn over
  - EBITDA - Earnings before interest, taxes, depreciation of its value, and amortisation
  - Debt on equity
  - Gross operating surplus/global costs
  - (Gross operating surplus / Turn over) * 100
- Qualitative Rating
  - Qualitative rating about shareholders contribution
  - Favorable economic market
  - Sector will increase
  - Management quality
  - Hold by a bigger company
  - CEO involved
  - Help from the group on legal

Exploratory Analysis

Example on Turnover

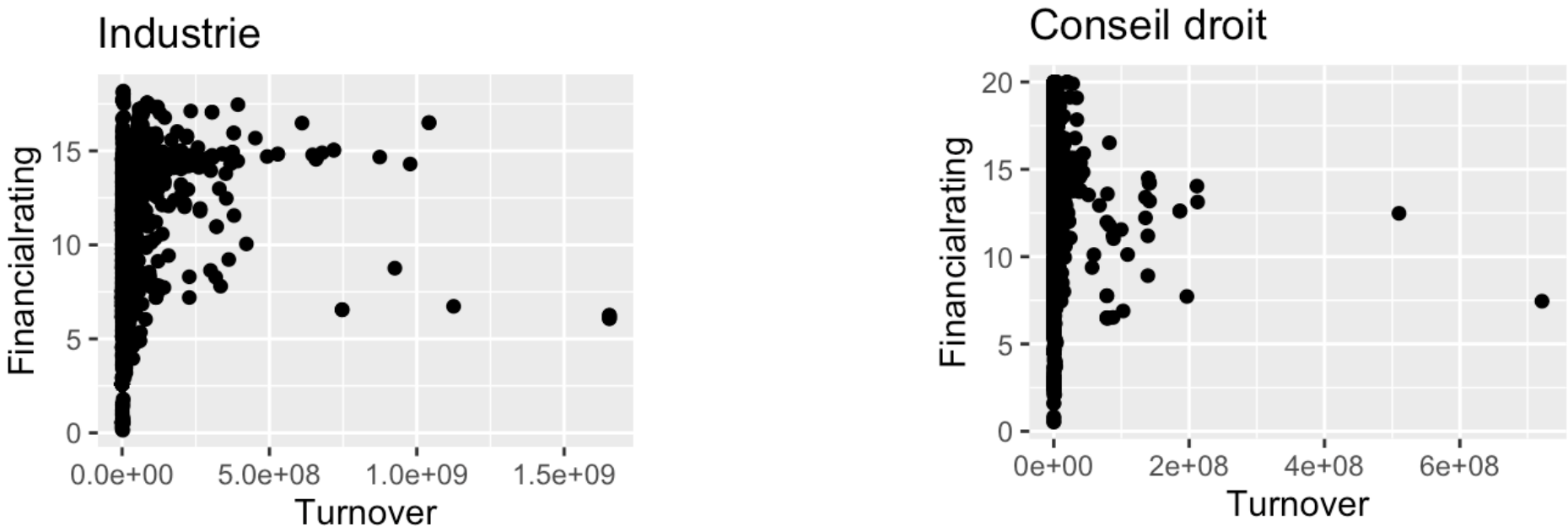

Figure 2: Scatter Plots for Turnover on Financial Rating

- Scatter plots are highly skewed on the left
  - High zero inflation - banks do not normally consider lending money to companies with zero Turnover
  - Zero values possibly represent incomplete information

Transformations

- Visualisation : look at the scatter plots
- Treatment of outliers : remove values above the 95th and below the 5th quantiles
- Log transformation : on strictly positive values
- Treatment of zero values : creation of a binary variable

Transformations

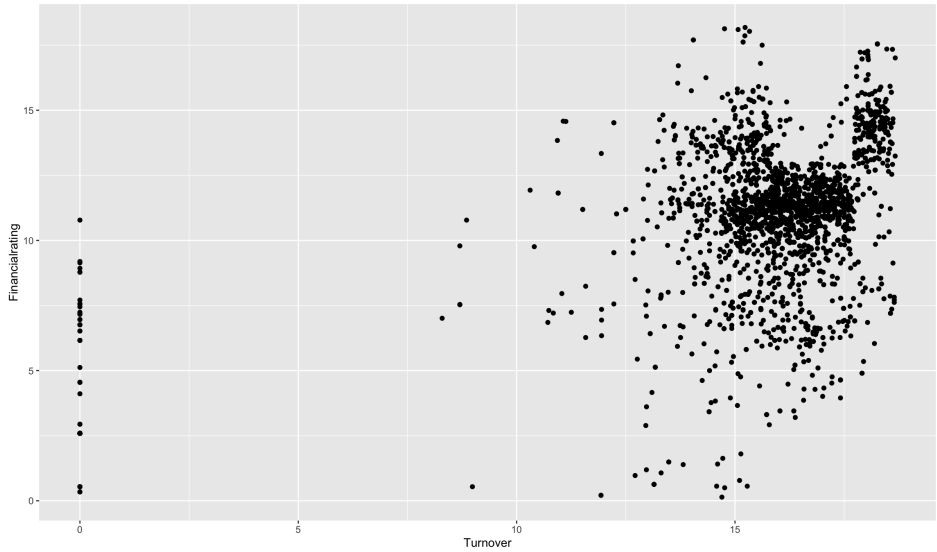

Figure 3: Scatter Plots for Turnover on Financial Rating after transformation

- Zero values needed to be treated differently from the positive values
- Data no longer concentrated around one value
- Positive relation between Financial Rating and Turnover

IV.Analysis

Model Specification: Distributional Assumption

- Employed the Generalised additive model (GAM) for Financial Rating, which has two assumptions
- First is a distributional one, where the response variable Y must come from the location-scale exponential family of distributions given by

$$f(y|\theta,\phi) = \exp\{w\frac{y\theta - b(\theta)}{\phi} + c(y,\phi)\}$$

where w are weights, θ is the location parameter, ϕ is the dispersion parameter, $b'(\theta) = \mathbb{E}(Y)$ and $c(y,\phi)$ is a constant term

- Encompasses a wide range of distributions, including the Gaussian, Binomial and Poisson distributions
- Histogram of Financial Rating is approximately Gaussian, so that is the specification we use

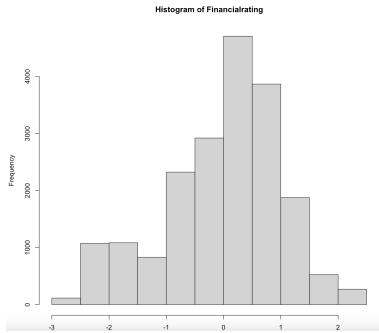

Figure 4: Histogram for Financial Rating

Model Specification: Structural Assumption

- Second assumption is a structural one: one has to assume the following relationship between the conditional mean and covariates

$$g(\mathbb{E}(Y|X_1, X_2, ..., X_m)) = \beta_0 + \sum_{i=1}^{m} f_i(X_i)$$

  where g is a link function between our covariates and our conditional mean, and f_i's are smooth functions to be estimated non-parametrically
- Functions estimated using Thin-Plate splines
- Conditional mean is thus

$$\mathbb{E}(Y|X_1, X_2, ..., X_m) = g^{-1}(\beta_0 + \sum_{i=1}^{m} f_i(X_i))$$

  where g^{-1} refers to the inverse image of our link function.

Metrics

- Evaluation of in-sample fit: adjusted R-squared and Generalised Cross-Validation score, where the former is calculated by

$$\bar{R}^2 = 1 - (1 - R^2)\frac{n-1}{n-m-1}$$

where m is the number of covariates and $R^2 = 1 - \frac{SSR}{SST}$ as usual, and the latter is given by

$$GCV(\lambda) = \frac{n \times SSR(\lambda)}{(n - tr(H)^2}$$

where $tr(H)$ is the trace of our hat matrix and SSR is the sum of squared residuals

- A higher adjusted R^2 and a lower GCV score is more desirable

Results: Industrie

A. parametric coefficients	Estimate	Std. Error	t-value	p-value
(Intercept)	11.5779	0.9310	12.4355	< 0.0001
zero_tover	-8.8013	14.9274	-0.5896	0.5555
zero_ebitda	-1.8702	0.2377	-7.8670	< 0.0001
zero_doe	-3.3308	0.1680	-19.8206	< 0.0001
zero_gos	0.0877	0.2698	0.3251	0.7451
zero_gos_100	1.6545	1.0656	1.5526	0.1207
B. smooth terms	**edf**	**Ref.df**	**F-value**	**p-value**
s(Turnover)	6.6268	7.5101	34.9199	< 0.0001
s(ebitda)	6.5002	7.6426	3.4458	0.0009
s(Debtonequity)	4.8667	5.9197	53.0050	< 0.0001
s(grossoperatingsurplusglobalcosts)	8.3821	8.8891	2.3535	0.0090
s(grossoperatingsurplusTurover100)	6.2229	7.4002	10.2040	< 0.0001
Observations	1939			
Adjusted R^2	0.762			
Deviance Explained	76.6%			
GCV	2.1323			

Table 1: GAM Results for Industrie

Results: Conseil Droit

A. parametric coefficients	Estimate	Std. Error	t-value	p-value
(Intercept)	21.2263	27.0260	0.7854	0.4323
zero.Turnover	-24.4866	54.5398	-0.4490	0.6535
zero.ebitda	-2.7774	0.3205	-8.6655	< 0.0001
zero.Debtonequity	0.5280	0.2399	2.2012	0.0278
zero.grossoperatingsurplusglobalcosts	1.1039	0.2601	4.2439	< 0.0001
zero.grossoperatingsurplusTurover100	4.6375	1.2044	3.8504	0.0001
B. smooth terms	**edf**	**Ref.df**	**F-value**	**p-value**
s(Turnover)	7.4590	8.0900	4.6991	< 0.0001
s(ebitda)	7.8650	8.6252	3.0308	0.0027
s(Debtonequity)	8.5043	8.9258	19.2991	< 0.0001
s(grossoperatingsurplusglobalcosts)	8.0697	8.7433	6.1876	< 0.0001
s(grossoperatingsurplusTurover100)	6.4218	7.5600	6.8493	< 0.0001
Observations	1820			
Adjusted R^2	0.725			
Deviance Explained	73.1%			
GCV	6.543			

Table 2: GAM Results for Conseil Droit

Prediction Error

- In addition to evaluating the in-sample fit of our model, we also evaluate the predictive accuracy of our model
- We do so by performing cross validation by splitting into a 80% training set and 20% test set
- We then calculate the root mean-squared prediction error using the following formula

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2}{n}}$$

  where $\hat{Y}_i$ refers to the prediction of our response variables using our model.
- We obtain the following results:

Industrie	2.295246
Conseil Droit	2.421836

Table 3: Root Mean Squared Error for Industrie and Conseil Droit

Comments

- We can see the smoothed terms are significant for all covariates in both groups
- Some of the binary variables (for the zero values) weren't significant, which is surprising
- Although the adjusted R^2 are quite similar for both groups, the GCV for Conseil Droit is much higher
- Our mean-squared prediction error isn't too good, although we highly suspect that is due to the sparsity of the data

Qualitative Rating: Model Specification

- For qualitative rating, we used a simple linear regression model
- Why? Because it worked surprisingly well

We are fitting the following model (in matrix notation):

$$\mathbf{Y} = \mathbf{X}\beta + \epsilon$$

where $\mathbf{Y}$ is our $n \times 1$ matrix of response variables, $\mathbf{X}$ is our $n \times p$ matrix of explanatory variables, and $\epsilon \sim \mathcal{N}(\mu, \sigma^2 D)$ are our error terms. Standard least squares theory gives us the estimated coefficients

$$\beta = (\mathbf{X}^{'}\mathbf{X})^{-1}\mathbf{X}^{'}\mathbf{Y}$$

with the conditional mean being

$$\mathbb{E}(Y|X) = \mathbf{X}\beta$$

Qualitative Rating: Results I

	Dependent variable:
	Qualitativerating
Qualitativeratingaboutshareholderscontribution3	0.993***
	(0.019)
Qualitativeratingaboutshareholderscontribution5	1.587***
	(0.018)
Qualitativeratingaboutshareholderscontribution6	1.418***
	(0.025)
Qualitativeratingaboutshareholderscontribution7	1.934***
	(0.026)
Qualitativeratingaboutshareholderscontribution8	1.819***
	(0.024)
Qualitativeratingaboutshareholderscontribution10	2.195***
	(0.021)
Qualitativeratingaboutshareholderscontribution12	2.678***
	(0.019)
Qualitativeratingaboutshareholderscontribution14	3.072***

Qualitative Rating: Results II

	(0.039)
Qualitativeratingabouttransparency3	0.591***
	(0.039)
Qualitativeratingabouttransparency5	1.442***
	(0.117)
Qualitativeratingabouttransparency6	1.622***
	(0.031)
Qualitativeratingabouttransparency8	2.211***
	(0.049)
Qualitativeratingabouttransparency9	2.475***
	(0.029)
Qualitativeratingabouttransparency11	3.050***
	(0.029)
Qualitativeratingabouttransparency12	3.345***
	(0.031)
Qualitativeratingabouttransparency14	3.874***
	(0.035)
Qualitativeratingabouttransparency15	4.271***
	(0.029)

Qualitative Rating: Results III

Qualitativeratingabouttransparency17	4.824***
	(0.029)
Favorableeconomicmarket3	0.686***
	(0.039)
Favorableeconomicmarket5	1.312***
	(0.029)
Favorableeconomicmarket6	1.528***
	(0.058)
Favorableeconomicmarket7	1.893***
	(0.043)
Favorableeconomicmarket8	2.144***
	(0.034)
Favorableeconomicmarket10	2.733***
	(0.032)
Favorableeconomicmarket11	3.047***
	(0.043)
Favorableeconomicmarket12	3.282***
	(0.032)
Favorableeconomicmarket13	3.612***

Qualitative Rating: Results IV

	(0.033)
Favorableeconomicmarket14	3.853***
	(0.039)
Favorableeconomicmarket15	4.195***
	(0.032)
Favorableeconomicmarket17	4.781***
	(0.033)
Favorableeconomicmarket19	5.366***
	(0.034)
Favorableeconomicmarket20	5.983***
	(0.042)
Sectorwillincrease3	0.109***
	(0.022)
Sectorwillincrease5	0.109***
	(0.019)
Sectorwillincrease7	0.104***
	(0.021)
Managementquality3	0.883***
	(0.022)

Qualitative Rating: Results V

Managementquality6	1.754***
	(0.020)
Managementquality7	2.021***
	(0.033)
Managementquality9	2.610***
	(0.021)
Managementquality10	2.879***
	(0.021)
Managementquality13	3.763***
	(0.021)
Managementquality14	4.051***
	(0.021)
Managementquality17	4.917***
	(0.021)
Managementquality20	6.069***
	(0.021)
HoldbyabiggerFirm1	0.450***
	(0.007)
CEOinvolved1	0.187***

Qualitative Rating: Results VI

	(0.006)
Helpfromthegrouponlegal1	0.064^{***}
	(0.005)
Constant	-0.064^{***}
	(0.018)
Observations	25,354
R^2	0.989
Adjusted R^2	0.989
Residual Std. Error	0.336 (df = 25306)
F Statistic	$47{,}192.470^{***}$ (df = 47; 25306)
Note:	*p<0.1; **p<0.05; ***p<0.01

Comments

- We can see that basically all the levels for every variable are statistically significant
- Our adjusted R^2 is very high - almost 99%!
- We also evaluate the prediction error using the RMSE as above, and we get a value of 0.335, faring much better than our Financial Rating model

V.Shiny Application

Shiny Application

- Incorporation of climate risk
- Goal of Shiny Application: allow for climate variables to be considered in the future
- Should start collecting data on climate variables now!

VI.Conclusion

Conclusion

- Experience how to deal with ”real-world” data
- Came up with creative solutions
- Deployed a functioning web application on Shiny, and worked with many tools used in development, such as Github
- Sharpened our technical skills and learnt to apply and choose between the many different models

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