Corporate Goverance and Company Performance

Project Goals + Status

☑ An initial goal is to acquire the dataset, whether by contacting MM or using Bloomberg terminals available in UCD Quinn and Smurfit, and reproduce some of MM's results.

Done

☑ A central goal is to apply (regularized) regression, and classification-on-regression (i.e. thresholding on the real value predicted by regression) rather than straight classification, as the main analysis, and follow this with a careful discussion of the pros and cons, and the findings (e.g. correlation analysis, both linear and rank correlation).

Done

☑ A side goal is to consider alternative features and measures of performance, beyond Z and Q.

Tried Beneish M Score as a dependent variable. Various ESG variables from Bloomberg as independent variables

☐ A stretch goal is to investigate modern work in causality (Pearl, 2009, King et al., 2016) and attempt to apply it here. Any contribution to the task of proving causality, as opposed to correlation, would be a large contribution.

Implementing akelleh, and causalTree

M&M - Classification

Taking the data, algorithms and hypothesis put forward by MM and replicate results. Data used as is or with manipulations made by M&m. Results as per Table 1 and 2.

M&M - Regression

Taking same data, but not thresholding on dependent variables meaning this is a regression problem.

Causality

akelleh

Methodology - Causal DAG

Methodology - Causal Estimation

M&M make 8 statements about the effects of various corporate governance features on either Tobins Q or the Altman Z Score. This is the basis for my work on causal estimation, following this guide - https://github.com/akelleh/causality/tree/master/causality/estimation. The goal is to pick a treatment and effect, and measure the magnitude of the effect of the former on the latter. Uses propensity matching.

I've built a table per statement. The manipualtions I carry out to prepare each are:

- Impute the data to remove missing values. Taking just complete cases is infeasable especailly for sxxp and eebp datasets, since there are so few cases without missing data.
- Scale all columns apart from the treatment and control. Speed up algorithm runtime, seems to be justified in terms of . . . ..

Called using something like;

```
ATE_results = matcher.estimate_ATE(
  data,
  treatment,
  target,
  {'P.B': 'c', 'Asset':'c', 'Tax':'c', 'P.E':'c'}, #to control for
  bootstrap=True
)
```

Also includes some plotting to show how good the matching process was.

For results, see Table 2.

causalTree

Table 1: MM Classification Results - Tobins Q as target

Algorithm	DataSet	Target	Correctly.Classified.Instances	Coverage.Of.cases	Precision.Class.0	Precision.Class.1	ROC.area
Adaboost	spx	Tobins.Q.class	0.8855422	NA	0.8674699	0.9036145	0.8855422
Adaboost	sxxp	Tobins.Q.class	0.8844221	NA	0.8300000	0.9393939	0.8846970
Adaboost	eebp	Tobins.Q.class	0.7878788	NA	0.7800000	0.7959184	0.7879592
J48	spx	Tobins.Q.class	0.8192771	NA	0.8607595	0.7816092	0.8211843
J48	sxxp	Tobins.Q.class	0.8793970	NA	0.8367347	0.9207921	0.8787634
J48	eebp	Tobins.Q.class	0.6767677	NA	0.8085106	0.5576923	0.6831015

Table 2: MM Classification Results - Altman Z as target

Algorithm	DataSet	Target	Correctly.Classified.Instances	Coverage.Of.cases	Precision.Class.0	Precision.Class.1	Precision.Class.2	ROC.area
Adaboost	spx	Altman.Z	0.8273381	NA	0.7142857	0.6315789	0.8888889	0.8556867
Adaboost	sxxp	Altman.Z	0.7770701	NA	0.8666667	0.6578947	0.8076923	0.8186984
Adaboost	eebp	Altman.Z	0.6923077	NA	0.3333333	0.5151515	0.8571429	0.7760000
J48	spx	Altman.Z	0.6834532	NA	0.3750000	0.3333333	0.7961165	0.6622580
J48	sxxp	Altman.Z	0.6878981	NA	0.5500000	0.4594595	0.8000000	0.7829983
J48	eebp	Altman.Z	0.6282051	NA	0.0000000	0.3333333	0.7413793	0.6992225

Table 3: akelleh Estimation Results

dataset	treatment	target	results
spx	Indep.Lead.Dir.Fincl..l	AZS	(-0.48126852399043463, -0.43435592738302015, -0.38972494514119399)
spx	Feml.CEO.or.Equiv	Tobins.Q	(-0.10126279335439194, 0.012848126155105874, 0.12824127721356948)
spx	X..Women.on.Bd	Tobins.Q	(0.11442235071138444, 0.1601459138176336, 0.20621396523499541)
sxxp	Indep.Lead.Dir.Feml.CEO.or.Equiv	Tobins.Q	(-0.074067123529340029, -0.028348354835763347, 0.012416082088477042)
sxxp	X..Women.on.Bd	Tobins.Q	(-0.18509495129967421, -0.13146459101319122, -0.085012004750609257)
eebp	BOD.Age.Rng	Tobins.Q	(-0.17513949067428736, -0.06049739831209239, 0.044424480674329032)
eebp	Fincl.l.treatment	Tobins.Q	(-0.13761563029896531, -0.027686073658574183, 0.074156162497339778)
eebp	Indep.Chrprsn.Feml.CEO.or.Equiv	AZS.class.Binary	(0.3880723356677665, 0.48173832421819107, 0.58578958829450489)