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 trying to replicate. Results as per Table 1.

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

```
## Warning in .local(conn, statement, ...): Decimal MySQL column 4 imported as
## numeric
```

Table 1: MM Classification Results

Algorithm	DataSet	Target	avg_accuracy	avg_coverage	avg_precision_0	avg_precision_1	avg_roc_area
Adaboost	eebp	AZS.class	0.6923077	NA	0.1250000	0.6800000	0.7760000
Adaboost	eebp	Tobins.Q.class	0.7878788	NA	0.7800000	0.7959184	0.7879592
Adaboost	spx	AZS.class	0.8057554	NA	0.8421053	0.3461538	0.8461144
Adaboost	spx	Tobins.Q.class	0.8855422	NA	0.8674699	0.9036145	0.8855422
Adaboost	sxxp	AZS.class	0.7770701	NA	0.4642857	0.5952381	0.8186984
Adaboost	sxxp	Tobins.Q.class	0.8844221	NA	0.8300000	0.9393939	0.8846970
J48	eebp	AZS.class	0.6495726	NA	0.0555556	0.4182686	0.6745579
J48	eebp	Tobins.Q.class	0.7239057	NA	0.7226701	0.7282086	0.7254393
J48	spx	AZS.class	0.7062350	NA	0.5308566	0.1742552	0.7419076
J48	spx	Tobins.Q.class	0.8363454	NA	0.8253275	0.8461488	0.8357381
J48	sxxp	AZS.class	0.6804671	NA	0.6237257	0.4849322	0.7963759
J48	sxxp	Tobins.Q.class	0.8643216	NA	0.8627529	0.8670640	0.8649085

Table 2: 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)