

The Relationship Between Corporate Governance and Company Performance

New Factors, New Models, New Approaches to Causality

Conor Reid

Dr. James McDermott & Dr. Miguel Nicolau

UCD Michael Smurfit Graduate Business School

conor.reid@ucdconnect.ie

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Overview

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Motivation and Previous Work

Corporate governance models vary widely across firms, and there is much debate on the impact of these differing styles on company performance.

- How can these features be optimised for best performance?
- What defines *best performance*?

Moldovan and Mutu (2015) attempted to answer these questions. They:

- Acquired data from the Bloomberg financial data repository.
- Tobins Q Score and Altman Z Score for success.
- Worked to learn explanatory and predictive models.
- Proposed rules for success.



Motivation and Previous Work

Moldovan and Mutu (2015):

- ✓ Identified a number of correlations across multiple algorithms and measures.
- ✗ Thresholded on continuous dependent variables.
- ✗ Unexplored algorithms and techniques.
- ✗ Correlation \neq Causation.

Other Work

- Holland (1986) discusses statistical models for causal inference.
- Pearl and Verma (1995), Pearl (2009) discuss causality extensively.



Approach

My Approach

- Reproduce some results of Moldovan and Mutu (2015).
- Integrate auxiliary independent and dependent covariates, e.g:
 - Ind CEO compensation
 - Ind Environmental & social impact disclosure
 - Dep Beneish M-Score
- Apply modern causal research.



My Methods

- Reproduce :
Using the same data, implement Adaboost and J48 [C5.0], as well as Regularised Linear Regression.
- Auxiliary Features :
Use Bloomberg repository to extract, merge using R.
- Causal Research :
Using modified data, implement Propensity Score Matching.



Results - CEO Compensation

Dataset

S&P 500

Dependent Variable

Tobins Q Score

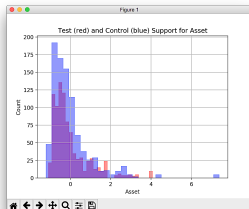
Treatment

CEO Comp > median(CEO Comp)? 1 : 0

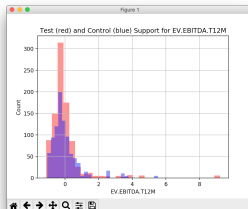
Estimate (% Δ)

(-0.06 ~ -0.11)

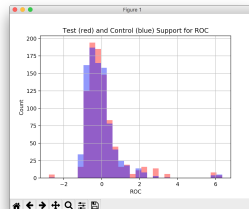
Matching Plots



(a) Asset



(b) EBITDA 12Mth



(c) ROC



Results - Indep Lead Director and Financial Leverage

Dataset

STOXX Europe 600

Dependent Variable

Altman Z Score

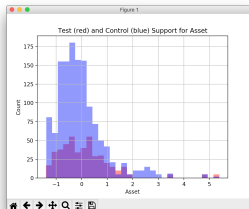
Treatment

(Indep Lead Dir & Financial Leverage > 2.5)? 1 : 0

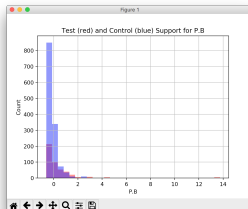
Estimate (% Δ)

(-0.24 ~ -0.30)

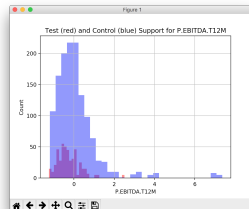
Matching Plots



(d) Asset



(e) P/B



(f) EBITDA



Academic Contribution

Athey (2017) asks *...whether a given problem can be solved using only techniques for prediction, or whether statistical approaches to estimating the causal effect of an intervention are required.*

Examining and applying causal analysis to this domain, with the aim of strengthen existing findings.

Business Contribution

Contribution to the literature on corporate governance best practice.



Conclusions

- Verified existing correlations with equivalent accuracy, and re-modelled the problem more appropriately.
- Integrated new features, facilitating new insight.
- Identified a subset of existing correlations with causal merit.



Dataset

- Include other markets, or poorly performing companies.
- Other data sources to fill in missing data.
- Integrate historical data.

Techniques

- Explore the *back-door criterion* (Pearl (2009)).



References

- Athey, S. (2017). Beyond prediction: Using big data for policy problems. *Science*, 355(6324):483–485.
- Holland, P. W. (1986). Statistics and causal inference. *Journal of the American statistical Association*, 81(396):945–960.
- Moldovan, D. and Mutu, S. (2015). Learning the relationship between corporate governance and company performance using data mining. In *International Workshop on Machine Learning and Data Mining in Pattern Recognition*, pages 368–381. Springer.
- Pearl, J. (2009). *Causality*. Cambridge university press.
- Pearl, J. and Verma, T. S. (1995). A theory of inferred causation. *Studies in Logic and the Foundations of Mathematics*, 134:789–811.





The Relationship Between Corporate Governance and Company Performance

Conor Reid - MSc Business Analytics

Supervisors - Dr. James McDermott and Dr. Miguel Nicolau

Objective

This study aims to continue the work of Moldovan and Mutu (2015), who studied the relationship between corporate governance and economic performance. They were able to identify numerous *if-this-then-that* style rules, which this study first aims to reproduce before extending by applying causal analysis.

Data

Moldovan and Mutu (2015) used a dataset scraped from the Bloomberg data repository, which was also used here. Three stock indexes are covered: the S&P, the STOXX 300 and 600. To this, auxiliary features were added (CEO pay etc).

Methods

Moldovan and Mutu (2015) carried out classification on two thresholded continuous metrics; the Tobins Q and Altman Z score. This study replicates this, as well as performing regression on the non-thresholded values. Finally, causal research is applied (propensity score matching) with the aim of identifying causal influences in the data.

Results

The results of this study are split into three categories, with elements of each outlined separately below.

Classification

The table below shows the performance of one of the algorithms used in this study, verses the performance achieved by Moldovan and Mutu (2015).

Dependent Variable : Tobin's Q					
Algorithm : Adaboost M1					
Study	Index	Accuracy (%)	Precision Class 0	Precision Class 1	ROC
M&M	SPX	89.72	0.89	0.905	0.957
Current	SPX	93.38	0.95	0.915	0.933
M&M	SXXP	88.24	0.891	0.874	0.946
Current	SXXP	94.47	0.961	0.929	0.945
M&M	EEBP	81.82	0.823	0.813	0.889
Current	EEBP	84.85	0.88	0.816	0.848

Table 1: Classification Results - Tobin's Q with Adaboost M1

Overall, results are very much in line with minimal improvements made in some areas.

Regularised Linear Regression

Figure 1 relates to the SXXP dataset, with the Tobin Q score as the dependant variable. Regularised regression allows the variance of the loss function, and thus gives control over the exact implementation of the regression (Ridge, Lasso or in-between). The left hand plot shows the suppression of the variable coefficients towards zero with increasing λ , and on the right the corresponding MSE evolution with changing λ .

Contact Information

- Conor Reid - MSc Business Analytics (Part Time)
- conor.reid@ucdconnect.ie

Here, results for pure Lasso and Ridge regression are shown.

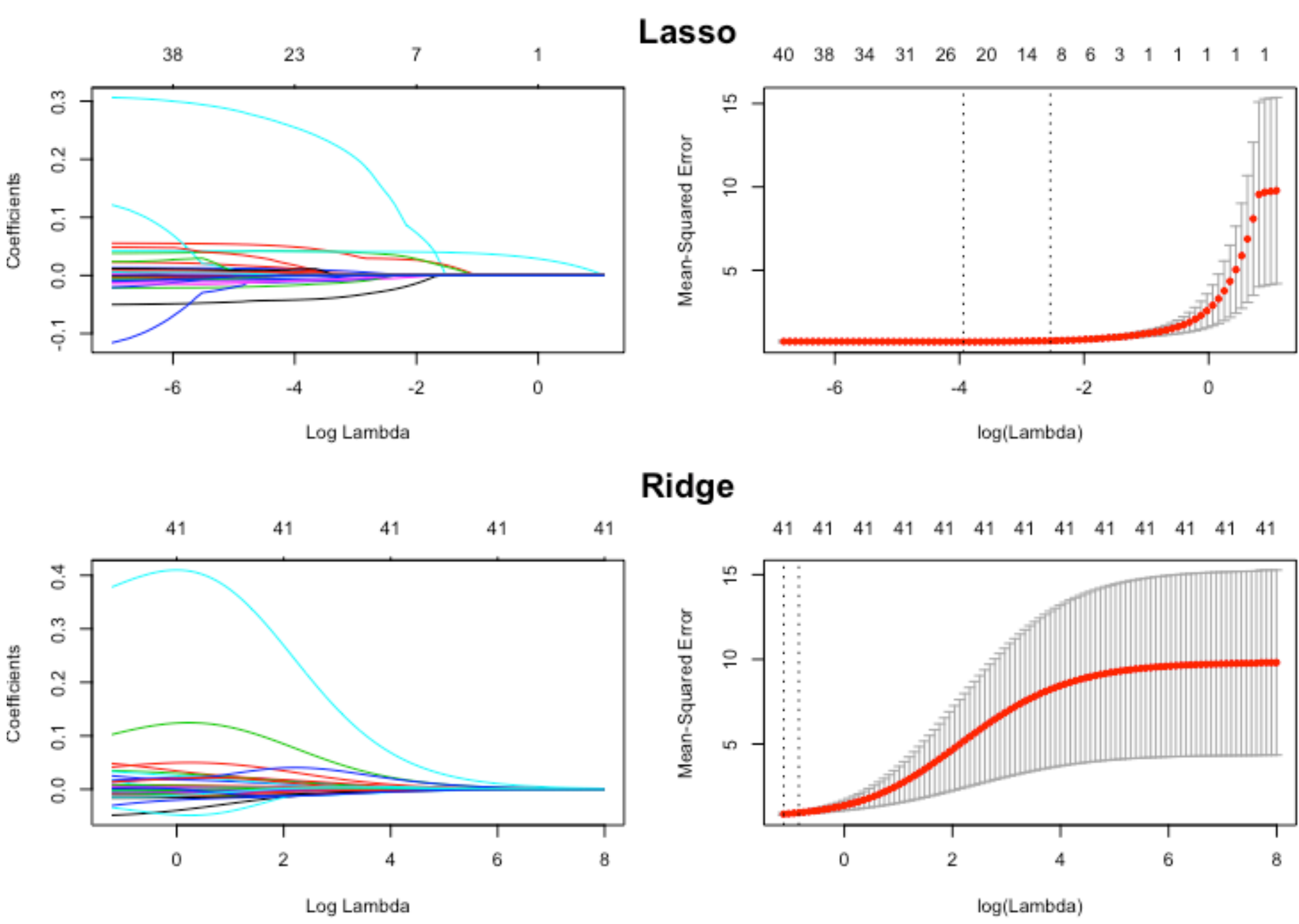


Figure 1: Regression Results - Tobins Q with the SXXP dataset

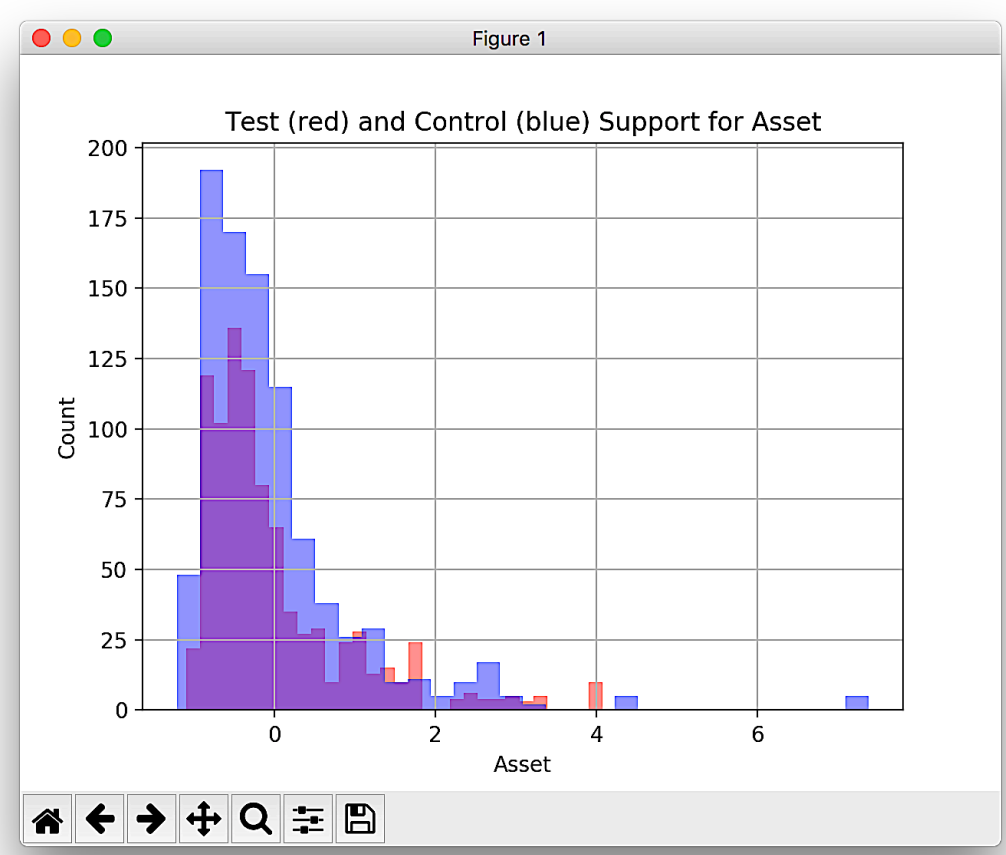
Clearly, as λ increase the model simplifies, however this is associated with an increase in MSE. This exemplifies the tradeoff between model interpretability and performance involved here.

Causal Inference

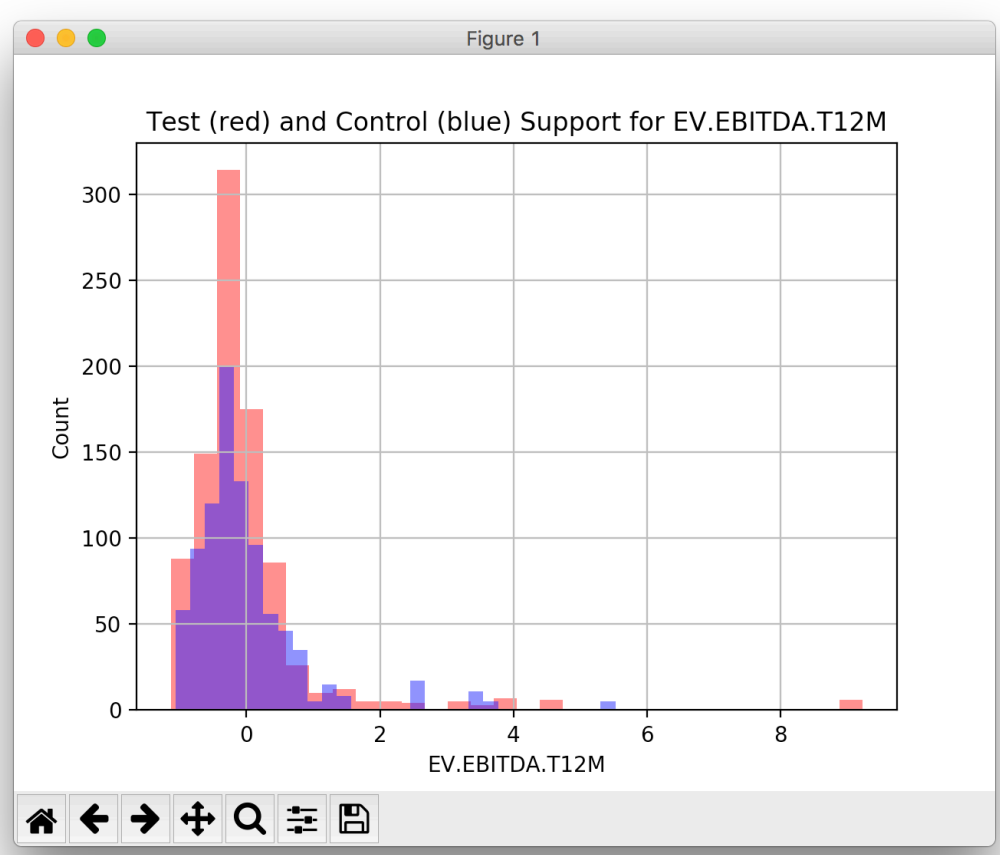
Below is an example result from the causal stage of this study.

Dataset	S&P 500
Dependent Variable	Tobins Q Score
Treatment	CEO Comp > median(CEO Comp)? 1 : 0
Estimate (% Δ)	(-0.06 ~ -0.11)

This can be interpreted as; CEO compensation above the median causes a decrease in Tobins Q by between 6% and 11%. Below, two (of many) sample matching plots are shown.



(a) Asset



(b) EBITDA 12Mth

Conclusions

Previously identified *if-this-then-that* style rules for corporate governance best practice have been verified, by both replicating that previous study as well as reframing it in a more natural way as a regression problem. By utilising cutting edge causal techniques, a subset with causal merit were identified. The results of this study contribute to a growing literature base on corporate governance and its effects on economic outcomes.

References

- [1] Moldovan, D. and Mutu, S. (2015). Learning the relationship between corporate governance and company performance using data mining. In *International Workshop on Machine Learning and Data Mining in Pattern Recognition*, pages 368–381. Springer.