

How important is corporate governance? Evidence from machine learning

Ian Gow¹ David Larcker²
Anastasia Zakolyukina³

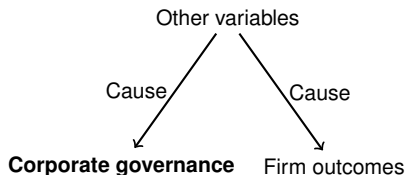
¹University of Melbourne

²Stanford Graduate School of Business

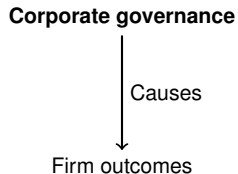
³University of Chicago Booth School of Business

Two views on governance research

Governance is an endogenous choice



Governance is "out-of-equilibrium"



Causal claims

- ▶ To infer causality, research often uses observational data¹
“There is some evidence, both in our sample and from other authors, that weak shareholder rights **caused poor performance** in the 1990s.”
- ▶ . . . controls for firm characteristics
“While our sample does not include a natural experiment to **identify G as the cause of operational differences**, we attempt to control for ‘expected’ cross-sectional differences . . . ”
- ▶ . . . causal stories loaded with cautionary language
“Since this is an experiment without random assignment, **no analysis of causality can be conclusive**”

¹Quotes from Gompers et al. (2003)

Mixed results: Board independence

- ▶ Increases firm value (Rosenstein and Wyatt, 1990)
- ▶ Decrease firm performance (Agrawal and Knoeber, 1996)
- ▶ No relation (e.g., Hermalin and Weisbach, 2003)
- ▶ Subsequent research has refined analysis
 - ▶ social ties to CEOs (e.g., Hwang and Kim, 2009)
 - ▶ prior favorable views of the firm (e.g, Cohen et al., 2012)
 - ▶ connections to CEOs (e.g., Fracassi and Tate, 2012)
 - ▶ cost of information (Duchin et al., 2010)

This paper

- ▶ Measurement and prediction
 - ▶ Paper is intellectual descendant of Larcker, Richardson, and Tuna (2007) and Daines, Gow, and Larcker (2010)
- ▶ Casual effects
 - ▶ Re-evaluate broad research approach on its own terms
 - ▶ Takes results at face value and **puts aside endogeneity**
 - ▶ If causality holds, causal relations should also be predictive

Out-of-sample prediction via machine learning

- ▶ Flexible measure of corporate governance
- ▶ Exploit the link between explanation and prediction
 - ▶ **Causal explanation must also be predictive on new data**
 - ▶ E.g., Hempel and Oppenheim (1948), Freedman (1991), Manski (2009), Watts (2014), Yarkoni and Westfall (2017), Hofman et al. (2017)
- ▶ Evaluate upper bound of predictability for firm outcomes

Prediction benchmarks

- ▶ Uninformed baseline, i.e., an average outcome
- ▶ Firm-characteristics-only models
- ▶ Firm- and corporate-governance-characteristics models

Data sources

- ▶ FactSet's SharkRepellent for takeover defences
- ▶ WhaleWisdom for institutional holdings
- ▶ Equilar for compensation and board structure
- ▶ AuditAnalytics for litigation and bankruptcies
- ▶ CRSP and Compustat for firm characteristics

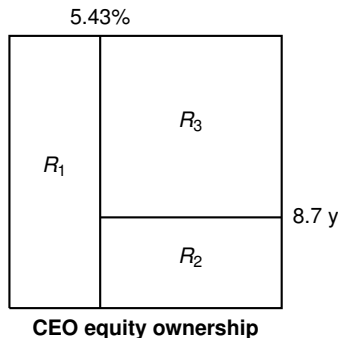
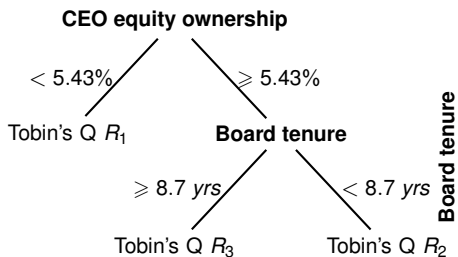
Over a hundred of governance features

- ▶ Institutional investor holdings
- ▶ Anti-takeover provisions
- ▶ Executive compensation
- ▶ Board's financial expertise
- ▶ Board characteristics

Prediction models

- ▶ Boosted regression trees (Friedman, 2001)
- ▶ Rolling cross-validation for tree depth and model size
 - ▶ depth (highest level of interactions) {1, 2, 3, 5, 7}
 - ▶ shrinkage 0.01
 - ▶ maximum number of trees 50,000
- ▶ Last three years as a test sample
- ▶ Use features at t to predict outcomes at $t + 1$ or $t + 3$

Boosting with trees



Models for restatements

Model	$t + 1$			
	Obs.	Tree depth	Trees	Error
Models with firm characteristics				
Firm	31,872	5	160	0.221
Firm, All govern.	31,872	7	215	0.213
Models without firm characteristics				
Inst. hold.	31,872	7	365	0.244
Anti-takeover	31,872	7	190	0.247
Comp.	31,872	2	900	0.229
Fin. expert	31,872	3	405	0.240
Board	31,872	3	1,490	0.228
All govern.	31,872	2	1,120	0.221

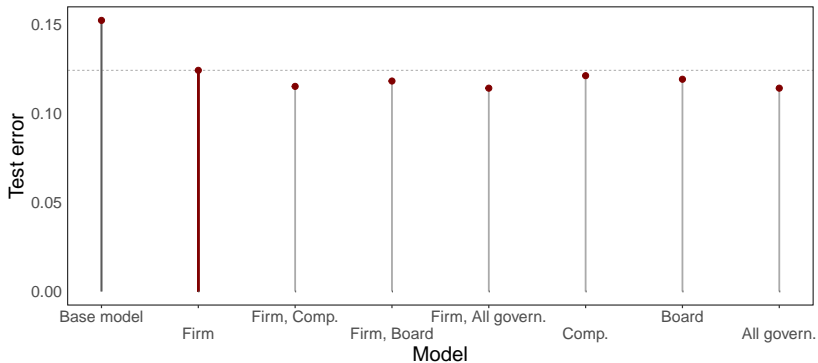
Models for return on assets, adj.

Model	$t + 1$			
	Obs.	Tree depth	Trees	Error
Models with firm characteristics				
Firm	37,345	3	1,050	0.086
Firm, All govern.	37,345	3	1,380	0.086
Models without firm characteristics				
Inst. hold.	37,345	1	2,350	0.159
Anti-takeover	37,345	5	660	0.167
Comp.	37,345	7	9,700	0.148
Fin. expert	37,345	2	640	0.166
Board	37,345	7	23,500	0.149
All govern.	37,345	7	42,700	0.138

Models for S&P credit rating

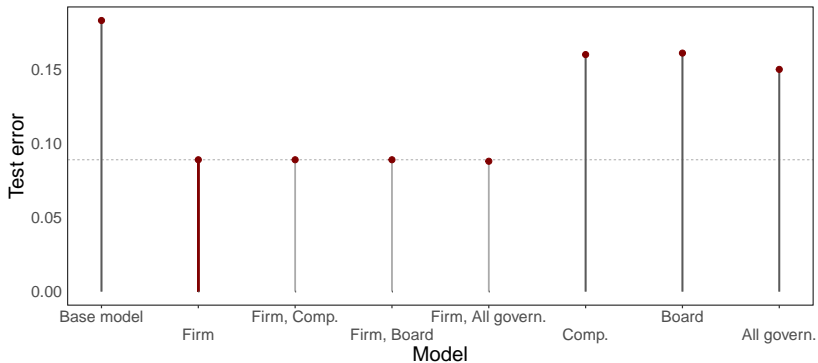
Model	$t + 1$			
	Obs.	Tree depth	Trees	Error
Models with firm characteristics				
Firm	12,969	7	5,100	0.562
Firm, All govern.	12,969	7	20,650	0.486
Models without firm characteristics				
Inst. hold.	12,969	5	590	0.969
Anti-takeover	12,969	5	3,550	1.057
Comp.	12,969	7	12,000	0.723
Fin. expert	12,969	2	1,170	0.959
Board	12,969	7	37,850	0.686
All govern.	12,969	7	40,850	0.618

Test errors for restatements



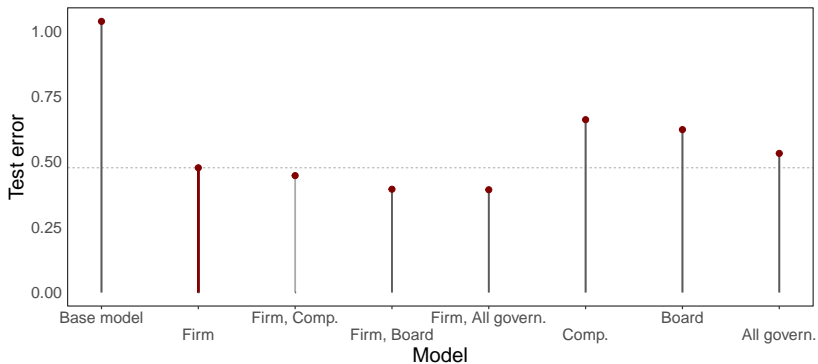
- ▶ No statistically significant improvements over firm characteristics only

Test errors for return on assets, adj.



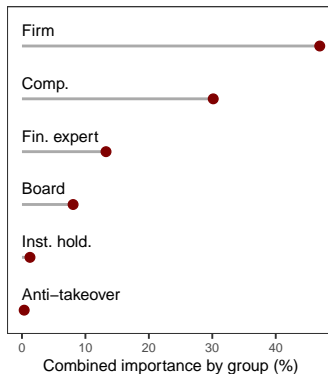
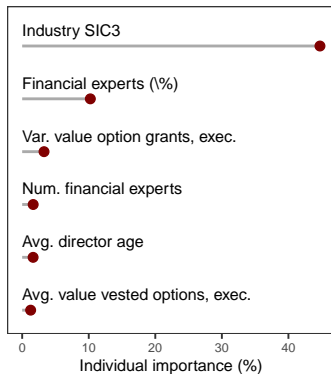
- ▶ Governance only worse than firm characteristics only

Test errors for S&P credit rating

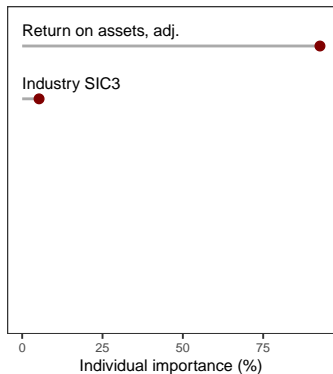


- ▶ Board characteristics **do** provide a meaningful improvement
- ▶ S&P evaluates governance of a firm as part of its process

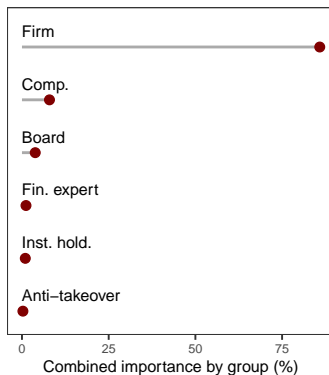
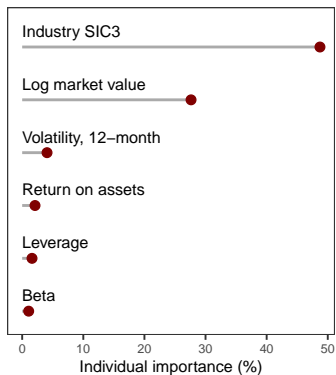
Variable importance for restatements



Variable importance for return on assets, adj.



Variable importance for S&P credit rating



Re-examination of Duchin et al. (2010)

- ▶ Re-examine credible instrumental-variable analyses
- ▶ Consider intention-to-treat specification
- ▶ Does random assignment to different treatments predict firm outcomes incremental to controls?

Re-examination of Duchin et al. (2010)

	Δ ROA	Δ ln(Q)	Mean return
Noncomply dummy	2.573* (1.422)	11.575* (6.225)	0.613*** (0.197)
InfoCost	-3.639* (2.112)	-41.892*** (8.435)	-0.660** (0.279)
Noncomply dummy \times InfoCost	-5.596* (2.973)	-31.487** (12.144)	-1.109** (0.420)
		...	
Observations	897	905	805
R ²	0.139	0.414	0.365
Adjusted R ²	0.085	0.378	0.321

- ▶ Intention-to-treat analyses
- ▶ *Noncomply dummy* is a firm being not in compliance with SOX in 2000
- ▶ *InfoCost* is an information cost index
- ▶ $\Delta X = X_{2005} - X_{2000}$

Re-examination of Duchin et al. (2010)

Y	Base MSE	MSE without IV	MSE with IV	MSE decrease	p-value
$\Delta \ln(Q)$	1905.784	1285.532	1280.694	4.838	0.200
ΔROA	60.229	56.418	56.538	-0.120	0.632
Mean return	1.304	0.978	0.978	0.000	0.502

- ▶ *Base MSE* only industry dummies
- ▶ *MSE without IV* control variables, industry dummies, and *InfoCost*
- ▶ *MSE with IV* adds the exogenous shifter *Noncomply dummy*
- ▶ *p-value* obtained via randomization inference

What do we learn (1)

- ▶ Causality should result in out-of-sample predictive ability
- ▶ If no predictive ability, causality is unlikely
 - ▶ But prediction focuses on **bias-variance tradeoff**
 - ▶ Causal effect of omitted variables is weak
 - ▶ No loss if most of the inf. is already in included variables

What do we learn (2)

- ▶ Null results are easy to find
 - ▶ ... but firm features still predict outcomes
- ▶ Governance matters in special cases
 - ▶ ... but ML allows for firm-governance-features interactions
- ▶ Inf. in governance is subsumed by firm features
 - ▶ ... but test against different firm features

Conclusions

- ▶ Corporate governance features do **not** improve on predictive ability over firm features
- ▶ No support for the existence of a strong causal effect of corporate governance on firm outcomes
- ▶ Cannot rule out that information in firm features (partially) subsumes information in corporate governance

References I

- Agrawal, Anup and Charles R Knoeber (1996). "Firm performance and mechanisms to control agency problems between managers and shareholders". In: *Journal of Financial and Quantitative Analysis* 31.3, pp. 377–397.
- Cohen, Lauren, Andrea Frazzini, and Christopher J Malloy (2012). "Hiring cheerleaders: Board appointments of "independent" directors". In: *Management Science* 58.6, pp. 1039–1058.
- Daines, Robert M, Ian D Gow, and David F Larcker (2010). "Rating the ratings: How good are commercial governance ratings?" In: *Journal of Financial Economics* 98.3, pp. 439–461.
- Duchin, Ran, John G Matsusaka, and Oguzhan Ozbas (2010). "When are outside directors effective?" In: *Journal of Financial Economics* 96.2, pp. 195–214.
- Fracassi, Cesare and Geoffrey Tate (2012). "External networking and internal firm governance". In: *Journal of Finance* 67.1, pp. 153–194.
- Freedman, David A (1991). "Statistical models and shoe leather". In: *Sociological Methodology*, pp. 291–313.
- Friedman, Jerome H (2001). "Greedy function approximation: A gradient boosting machine". In: *Annals of Statistics*, pp. 1189–1232.
- Gompers, Paul, Joy Ishii, and Andrew Metrick (2003). "Corporate governance and equity prices". In: *Quarterly Journal of Economics* 118.1, pp. 107–156.
- Hempel, Carl G and Paul Oppenheim (1948). "Studies in the Logic of Explanation". In: *Philosophy of Science* 15.2, pp. 135–175.

References II

- Hermalin, Benjamin and Michael Weisbach (2003). "Boards of directors as an endogenously determined institution: A survey of the economic literature". In: *Economic Policy Review* 9.Apr, pp. 7–26.
- Hofman, Jake M, Amit Sharma, and Duncan J Watts (2017). "Prediction and explanation in social systems". In: *Science* 355.6324, pp. 486–488.
- Hwang, Byoung-Hyoun and Seoyoung Kim (2009). "It pays to have friends". In: *Journal of Financial Economics* 93.1, pp. 138–158.
- Larcker, David F., Scott A. Richardson, and İrem Tuna (2007). "Corporate governance, accounting outcomes, and organizational performance". In: *The Accounting Review* 82.4, pp. 963–1008.
- Manski, Charles F (2009). *Identification for prediction and decision*. Harvard University Press.
- Rosenstein, Stuart and Jeffrey G Wyatt (1990). "Outside directors, board independence, and shareholder wealth". In: *Journal of Financial Economics* 26.2, pp. 175–191.
- Watts, Duncan J (2014). "Common sense and sociological explanations". In: *American Journal of Sociology* 120.2, pp. 313–351.
- Yarkoni, Tal and Jacob Westfall (2017). "Choosing prediction over explanation in psychology: Lessons from machine learning". In: *Perspectives on Psychological Science* 12.6, pp. 1100–1122.