Working Paper No. 22-16

How important is corporate governance? Evidence from machine learning

Ian D. Gow
University of Melbourne

David F. Larcker
Stanford University

Anastasia A. Zakolyukina
University of Chicago Booth School of Business

How important is corporate governance? Evidence from machine learning

Ian D. Gow David F. Larcker Anastasia A. Zakolyukina*

March 31, 2023

ABSTRACT

We use machine learning to assess the predictive ability of over a hundred corporate governance features for firm outcomes, including financial-statement restatements, class-action lawsuits, business failures, operating performance, firm value, stock returns, and credit ratings. We discover that adding corporate governance features does not improve the predictive accuracy of models over that of models constructed using only firm characteristics. Our results confirm the challenges in constructing measures of corporate governance with predictive value suggested in prior research. These results also raise doubts about the existence of strong causal effects of corporate governance on firm outcomes studied in prior research.

*We thank Tengyuan Liang, John Core, Michael Weisbach (discussant), and seminar participants at the Northwestern Law School Law and Economics Colloquium, MIT, NBER Big Data and Securities Markets Conference for helpful comments. We are grateful to the authors of Duchin et al. (2010) and Atanasov and Black (2021) for generously sharing their data and code with us. We also thank Vadim Cherepanov and Jingyu Zhang for outstanding research support. Larcker acknowledges support from the Stanford Rock Center for Corporate Governance. Zakolyukina acknowledges financial support from the IBM Corporation Faculty Research Fund, William Ladany Faculty Research Fund, and the University of Chicago Booth School of Business, and research support from the University of Chicago Research Computing Center. Gow is at the University of Melbourne. Larcker is at Stanford Graduate School of Business and Hoover Institution. Zakolyukina is at the University of Chicago Booth School of Business. Send correspondence to Anastasia A. Zakolyukina, University of Chicago Booth School of Business, 5807 S. Woodlawn Ave., Chicago, IL, 60637. Email: anastasia.zakolyukina@chicagobooth.edu.

1. Introduction

Three broad interrelated questions have long been prominent in corporate governance research: measurement, prediction, and causation. Researchers and practitioners have been interested in the *measurement* of corporate governance for at least two reasons. First, researchers and practitioners have been interested in constructing measures of corporate governance that can be used to *predict* unfavorable corporate outcomes, such as financial-statement restatements, class-action lawsuits, business failures, or declines in operating performance, firm value, and credit rating. Second, researchers are generally interested in causal questions, such as whether worse corporate governance increases the probability of or *causes* unfavorable corporate outcomes.

The questions of measurement and prediction have often been pursued in concert. For example, Daines et al. (2010) examine whether commercial measures of corporate governance predict various firm outcomes and find very little evidence of these measures having predictive value. Larcker et al. (2007) report similar results using researcher-constructed measures of governance. As for causation, one important stream of the literature has looked for associations between corporate governance features and firm outcomes as evidence of causal effects. Papers in this literature typically condition these associations by including a variety of firm characteristics as control variables. For example, Gompers et al. (2003) find that "firms with stronger shareholder rights [a dimension of corporate governance] had higher firm value, higher profits, higher sales growth, lower capital expenditures, and made fewer corporate acquisitions." While they warn that, without random assignment of governance, their evidence does "not allow strong conclusions about causality," Gompers et al. (2003, pp. 209–210) do claim to find some evidence that "higher agency costs [caused by weaker shareholder rights] . . . [affecting] both capital expenditures and acquisition activity."

In this paper, we use machine learning to re-examine the broad research questions of measurement, prediction, and causation in corporate governance.[1] Mirroring the basic approach in the stream of literature that has examined *associations* between corporate governance attributes and firm outcomes, we examine whether corporate governance features have *predictive* value for subsequent firm outcomes incremental to firm characteristics. We collect comprehensive data on over a hundred corporate governance characteristics, including institutional investor holdings, anti-takeover provisions, executive compensation, and board characteristics such as financial expertise (e.g., Bhojraj and Sengupta, 2003; Larcker et al., 2007; Daines et al., 2010). We also collect data on firm characteristics drawn from prior literature. For firm outcomes, we draw on extant corporate governance research in considering financial-statement restatements (Dechow et al., 2011), class-action lawsuits (Rogers and Stocken, 2005), business failures (Campbell et al., 2008), operating performance (Daines et al., 2010), firm value (Daines et al., 2010), stock returns (Fama and French, 2015), and credit ratings (Daines et al., 2010). We train models that use current characteristics to predict future outcomes. We apply gradient boosting of regression trees (Friedman, 2001; Friedman et al., 2009), which easily accommodates both non-linearities and interactions between variables, and use cross-validation in the training data to set meta-parameters. We compare the predictive ability of models including corporate governance characteristics

[1] Internet Appendix A discusses research on CEO duality, board independence, and staggered boards as three examples studied in prior research.

against both a baseline model that uses the average outcome as the prediction, and also machine-learning models based solely on firm characteristics.

In our main analysis, we find that—for virtually all outcomes—including corporate governance characteristics does not improve the predictive ability of models over those that use firm characteristics alone. While machine-learning models based on firm characteristics alone outperform the baseline models, adding corporate governance characteristics generally does not yield statistically significant improvements in model performance. These results suggest that these corporate governance attributes have little or no causal effect on the firm outcomes, which undermines causal claims in association-based studies.

While many papers have given causal interpretations to documented associations, this approach has not gone without criticism. As acknowledged by Gompers et al. (2003), governance features result from complex choices by firms and are not randomly assigned. As such it is well-understood that associations *per se* do not provide reliable evidence of causal relations. For example, if trying to understand the effect of police on crime, a researcher who naively examined the association between police numbers and crime statistics across neighborhoods might be surprised to find a positive association instead of a predicted negative one.[2] Such an association could arise because factors that affect crime levels in a neighborhood also drive the number of police officers deployed there.

Many researchers have sought to use various so-called identification strategies to identify variation in corporate governance features that are plausibly random (or "as if" random) to draw more credible causal inferences. In terms of our crime example, if we could randomly manipulate the number of police in the neighborhoods under study and

[2]We thank Michael Weisbach, our discussant at the 2023 NBER Big Data and Securities Markets conference, for suggesting this example.

conjecture that additional police reduce crime, we would expect that the neighborhoods randomly assigned additional police should have lower subsequent crime rates than comparable neighbourhoods assigned to be controls. In this way, our conjectured causal relation could be expressed as a prediction of variation in future crime rates across treatment assignments. And failure of randomly assigned additional policing to predict such rates could be interpreted as either evidence against the existence of such a causal relation or that the causal effect is too small to be detected.

To illustrate how our basic approach can be applied in such settings, we re-examine the setting of Duchin et al. (2010). Duchin et al. (2010) use compliance with the requirements of Sarbanes-Oxley Act of 2002 (SOX) prior to SOX as an instrument for subsequent changes in the number of independent directors. They then examine the causal effects of such directors on firm performance, including tests of differential effects for firms with varying information cost. We apply our machine-learning approach to the setting of Duchin et al. (2010) to examine whether random assignment to different treatments predict firm outcomes incremental to the firm attributes included as controls by Duchin et al. (2010). Because valid identification strategies are typically specific to a given setting carefully constructed by the given research team, our analysis of the setting of Duchin et al. (2010) merely exemplifies how machine learning can be applied in settings where causal interpretations of empirical analyses are more credible. In our reanalysis of Duchin et al. (2010), we do not find evidence that exogenous shocks to board independence predict firm performance.

Our use of machine learning not only for prediction, but also to glean insights into causal relations draws on recent work connecting prediction and causation. Many social scientists and philosophers find it self-evident that causal explanation must also be predictive; that is, the knowledge identified by the causal mechanism can be used to predict an outcome on new data (e.g., Hempel and Oppenheim, 1948; Freedman, 1991; Manski, 2009). In terms of the police-and-crime example above, we would expect that, to the extent that exogenous increases in police numbers cause reduction of crime rates in those neighborhoods, that these increases should *predict* reduced crime.

Using machine-learning methods has a number of benefits relative to the methods more conventionally used in corporate governance research, which typically deduce causal effects from the presence of statistically significant coefficients in regression analyses. First, machine-learning methods are designed to reduce the potential for over-fitting. Recent years have seen an increase in concern that empirical results in social science are not reliable, often due to various factors that lead to published research documenting relations that are hard to reproduce in subsequent research (Ioannidis, 2005; Harvey, 2017).

Second, machine-learning methods are particularly useful in complex institutional settings where theory provides limited guidance on true causal relations. For example, while conventional wisdom suggests that independent directors increase firm value, researchers have struggled to find evidence of such effects (e.g., Hermalin and Weisbach, 1991). Duchin et al. (2010) argue that the relation between independent directors and firm value is more complex than assumed in prior research and show that independent directors increase firm value when information costs are low. Given the time that elapsed between early studies (e.g., Rosenstein and Wyatt, 1990; Hermalin and Weisbach, 1991) and Duchin et al. (2010), the insight of Duchin et al. (2010) was arguably non-obvious. In such settings, machine-learning can identify complex interactions between variables such as those documented in Duchin et al. (2010). The tree-based ensemble methods we use in this paper are particularly well-adapted to detecting interactions that improve the predictive ability of models.

Our results are, of course, subject to a number of caveats. First, our focus on easily measured and commonly used corporate governance characteristics may limit the predictive ability of models derived from them. It may be that dimensions of corporate governance less easily measured and observed by researchers have significant explanatory power for firm outcomes.

Second, our use of models based on firm characteristics as benchmark models may be problematic. If the causal effects of corporate governance attributes on firm outcomes are mediated by firm characteristics in our benchmark models, the incremental predictive value of governance attributes may be understated.[3] It is important to note that this caveat also applies to papers that include these firm characteristics as controls and we select these variables precisely because prior research has used these characteristics in this way. But to better understand this issue, we examine the performance of models based on corporate governance attributes alone. We find that these models do not perform better than the baseline models and, with the exception of compensation and board characteristics, have larger prediction errors. Compensation and board characteristics often outperform baseline models, but have accuracy that is similar or inferior to the models that use only firm characteristics. Firm characteristics is also the most important group of predictors.

Third, it is possible that causal relations between corporate governance and firm outcomes are too complex to be recovered by any association-based evidence from observational data. For example, the endogenous selection of corporate governance attributes

[3] Gow et al. (2016) provides a general discussion of when inclusion of controls reduces or increases bias.

is likely to confound analyses based on associations (Hermalin and Weisbach, 2003). Of course, as discussed above, this caveat applies to a significant portion of research on corporate governance. Additionally, our reanalysis of Duchin et al. (2010) demonstrates how our basic approach can also be applied in settings where credible identification strategies exist and our results in that setting are consistent with those in our main analysis.

Our paper contributes to our understanding of corporate governance in a number of ways. First, we contribute to the literature examining the predictive ability of corporate governance measures. Prior research (e.g., Gompers et al., 2003) has often used simple indexes, perhaps to avoid concerns about data-dredging or overfitting. Machine-learning approaches are explicitly designed to facilitate prediction and modern methods such as those we use are widely regarded as the state of the art for this purpose. The fitted values from the models we train using machine-learning methods can be viewed as measures of corporate governance. No paper that we know of has examined the predictive ability of machine learning–derived governance measures. Our results provide additional evidence on the difficulty of constructing meaningful and useful measures of corporate governance. Like Larcker et al. (2007) and Daines et al. (2010), we find that the predictive ability of corporate governance measures is somewhere between zero and very weak. Our results suggest that these findings generalize beyond the specific classes of governance measures that those papers study.

Second, our paper provides evidence regarding the existence and strength of causal effects of corporate governance on firm outcomes. In this regard, our paper draws on recent research in the social sciences that seeks to integrate explanatory and predictive modelling (Hofman et al., 2021) and to use prediction to test theories (Peysakhovich and

Naecker, 2017; Fudenberg et al., 2022; Agrawal et al., 2020). The failure of corporate governance measures to predict the kinds of outcomes studied in prior research suggests that either corporate governance theories offer little in terms of explanatory power for firm outcomes and that further work is needed to develop models with greater predictive power, or that the effect of corporate governance on firm outcomes, if any, is in fact too small to be detected even in large samples.

2. Causal models and out-of-sample predictive ability

2.1 Using prediction to test theories

Mixed findings on the relation between various corporate governance characteristics and firm outcomes question the existence of strong causal mechanisms claimed in some studies. Because understanding a phenomenon requires both causal explanation and prediction (e.g., Watts, 2014; Yarkoni and Westfall, 2017; Hofman et al., 2021), we propose leveraging out-of-sample predictive ability of corporate governance characteristics in assessing the plausibility of these causal claims. Corporate governance research typically does not test for predictive power of proposed causal models. It often assumes a model's explanatory power translates into its predictive power, which is not always the case (Shmueli, 2010). The basic idea is that, if a relation between a corporate governance characteristic and an outcome is causal, this characteristic should help predict the outcome out of sample by making prediction of the outcome more accurate. In other words, causality should result in out-of-sample predictive ability.

Prediction on out-of-sample data provides a harsher test than fitting many models on in-sample data (Freedman, 1991; Hofman et al., 2021). Low out-of-sample predictive ability of a model with good in-sample fit can be due to incompleteness of a theory or the irreducible noise of an outcome. Fudenberg et al. (2022) introduce an idea of theory "completeness," which is related to ideas in Peysakhovich and Naecker (2017). They use machine-learning-based prediction to isolate the irreducible error in an outcome and thus assesses an upper bound on how well one can predict an outcome using a given set of features. In our paper, the extent of predictive ability of machine-learning-based models that use corporate governance features would provide an upper bound on an amount of explainable variation in firm outcomes that can be achieved by the theory that uses these features.

2.2 Omitting causal factors and prediction

While the idea of leveraging out-of-sample prediction in testing causal models is appealing, prior research has established conditions under which an incomplete causal model predicts better than a true (complete) causal model (e.g., Hagerty and Srinivasan, 1991; Wu et al., 2007; Shmueli, 2010). This happens because prediction seeks to minimize the combination of bias and estimation variance as often captured by mean-squared errors (MSE). As given by Friedman et al. (2009), p. 223, MSE or the expected prediction error equals the sum of three elements: irreducible error, squared bias, and variance. The irreducible error is the variance of the noise in the outcome. This error cannot be avoided no matter how well the target function is estimated. The bias is the amount by which the average of the estimated target function differs from the true mean of the target function. This bias is the result of misspecifying the statistical model, e.g., using the incomplete model instead of the complete model. The variance is the variance of the estimated target function around its mean. This variance is the result of using a sample to estimate the target function.

The comparison of the MSEs from a complete versus an incomplete model suggests the following trade-offs (see Wu et al., 2007, for the linear case).[4] First, the omission of a causal variable increases the bias but decreases the variance of model predictions. If the omitted variable has little influence on the dependent variable causing only a small bias when omitted, excluding it from the model may cause a substantial decrease in the variance of predictions, so that the overall MSE also decreases, especially when the noise in the dependent variable is large. That is, if addition of corporate governance characteristics does not improve prediction errors, while the existence of a causal effect cannot be completely ruled out, these corporate governance characteristics have a trivial causal effect, if any. Second, there can be no loss in the predictive ability of the model if most of the information contained in the omitted variables is already contained in the included variables. This can happen when the causal effects of corporate governance are mediated by firm characteristics or vice versa. Third, the inclusion of irrelevant variables with zero effect on the dependent variable increases the variance and MSEs. That is, we could also observe deterioration in prediction errors if corporate governance is irrelevant for firm outcomes we consider.

[4]The complete set of conditions for the incomplete model to have lower MSE than the complete model is in Wu et al. (2007), p. 389 and p. 391: (1) the data are noisy, i.e., large irreducible noise; (2) the true absolute values of effects of omitted variables are small; (3) high correlation between omitted and included predictors; or (4) the sample size is small.

3. Data

We collect comprehensive data on over one hundred corporate governance characteristics from Equilar, WhaleWisdom, and FactSet with firm characteristics from Compustat, CRSP, and Audit Analytics. In addition to considering all governance features together, we also split them into groups: institutional investor holdings, anti-takeover provisions, compensation, board financial expertise, and board characteristics. The corporate governance characteristics mostly come from prior literature, e.g., Bhojraj and Sengupta (2003), Larcker et al. (2007), and Daines et al. (2010). We vary firm characteristics by the firm outcome examined, drawing from the extant literature in each case. For restatements of financial statements, we use Model 1 from Dechow et al. (2011). For class-action lawsuits, we use prediction model from Rogers and Stocken (2005). For business failures, we use prediction model from Campbell et al. (2008).[5] For stock returns, we use firm characteristics from the five-factor model from Fama and French (2015). For operating performance, firm value, and credit ratings, we use firm characteristics from Daines et al. (2010). Table A.1 provides definitions of the variables.

Our sample covers data for 2001–2016 period. The sample starts in 2001 because Equilar executive compensation and board characteristics coverage starts at that time. The sample ends in 2016 to allow for the two to three years it takes for an error in financial statements to be detected (Zakolyukina, 2018). Thus, our data set includes restatements revealed in 2019, which is the last pre-COVID-19 year, making our data complete with respect to pre-COVID-19 outcomes. For each firm outcome, we use the last three years of data as an

[5] Ogneva et al. (2020) provide details on computing the variables.

out-of-sample test set and the remaining data from earlier periods as a training set.

The corporate governance sub-groups are from different data sources and are defined in Table A.1. For institutional investor holdings in Table A.1, Panel A, we use WhaleWisdom[6] data on Form 13F holdings. For anti-takeover provisions in Table A.1, Panel B, we use FactSet's SharkRepellent[7] data on takeover defenses. For executive compensation in Table A.1, Panel C, board financial expertise in Panel D, and board characteristics in Panel E, we use Equilar[8] data on executive compensation, directors' characteristics and board committees' composition.

Table 1 provides descriptive statistics for each of the corporate governance sub-groups. These summary statistics are consistent with those reported in the prior literature. Our largest sub-group is compensation of CEO and non-CEO executives. This category includes means, variances, and ratios of various compensation measures. The next largest category is board characteristics with variables found to be important in the literature, e.g, number of directors appointed after a CEO takes office, number of directors over 69 years old, number of busy directors. The categories that follow are financial expertise of the board, e.g., number of financial experts, number of directors on audit and finance committees, anti-takeover provisions, e.g., the indicators for staggered board and poison pill, and institutional investor holdings, e.g., institutional ownership and blockholder.

Table A.1 also defines outcomes and firm characteristics for each outcome. For firm outcomes, data on restatements of financial statements, class-action lawsuits, and business failures are from Audit Analytics, and return on assets, firm value, stock returns, credit

[6]See https://whalewisdom.com/.
[7]See https://go.factset.com/marketplace/catalog/product/factset-corporate-governance.
[8]See https://www.equilar.com/.

ratings, and firm characteristics are from Compustat and CRSP. Table A.1, Panel F, provides details on firm characteristics included into the models for restatements of financial statements. We consider a broad category of restatement events as implemented in Terry et al. (2022) and based on Appendix 2 in Cheffers et al. (2014). These are restatements surrounded by events pointing to potential irregularities. For instance, these events include CEO or CFO dismissals resulting from internal investigations or suspected wrongdoing, auditor changes related to SEC inquiry or management unreliability, or overlap between the restated period and the violation period alleged by the Accounting and Auditing Enforcement Releases (AAERs) from Dechow et al. (2011). We require these events to happen within one year before or after the restatement. We also consider more severe restatement irregularities as defined in Hennes et al. (2008). According to their criteria, we search all of Audit Analytics restatement disclosure narratives for the words "fraud" or "irregularity," SEC or Department of Justice formal or informal investigations, or the discussion of independent investigations by an audit committee or a special committee. After automatic pre-screening for search terms, we read each relevant disclosure to make a final judgment about whether that disclosure can be classified as an irregularity. For restatement-related firm characteristics, we use Model 1 from Dechow et al. (2011), which includes accruals from Richardson et al. (2005), soft assets, indicator for debt or equity issuance, and growth in receivables, inventory, cash sales, and return on assets.

Table A.1, Panel G, provides details on firm characteristics included into the models for class-action lawsuits. We create an indicator variable for a fiscal year overlapping with a class-action period. For class-action-related firm characteristics, we use the model from Rogers and Stocken (2005) that includes firm size, share turnover, market beta, stock returns, return volatility, skewness of daily returns, minimum of the daily returns over the past 12-month period, indicators for bio-technology, computer hardware, computer software, electronics, and retailing industries. Table A.1, Panel H, provides details on firm characteristics included into the models for business failures. We define business failure as a firm failing within the next 3 years for the failure outcomes from Ogneva et al. (2020) such as bankruptcies and performance-related delistings. For failure-related firm characteristics, we use the model from Campbell et al. (2008) as implemented in Ogneva et al. (2020) that includes profit ratio, total liabilities to total assets, excess stock return, return volatility, size, cash to total assets, market-to-book ratio, and stock price.

Table A.1, Panel I, provides details on firm characteristics included into the models for return on assets. The only characteristics we include are lagged return on assets and the logarithm of market value as in Daines et al. (2010). Table A.1, Panel J, provides details on firm characteristics included into the models for firm value, that is, Tobin's Q. Following Daines et al. (2010), the only firm characteristic we include is lagged Tobin's Q. Table A.1, Panel K, provides details on firm characteristics included into the models for stock returns. We include firm characteristics from the five-factor model from Fama and French (2015), that is, the logarithm of market value, book-to-market ratio, operating profitability, and investment. Table A.1, Panel L, provides details on firm characteristics included into the models for credit ratings. The S&P credit rating is converted into numerical value following Ashbaugh-Skaife et al. (2006). Investment grade debt is an indicator variable for the credit rating at or above speculative grade BBB. Following Daines et al. (2010), we include the logarithm of market value, book-to-market ratio, return on assets, leverage, market beta, and stock return volatility computed over 12-month period.

Table 1 reports descriptive statistics for corporate governance, firm outcomes, and outcome-specific firm characteristics for the results reported in the main text of the paper. Table IA.1 in Internet Appendix reports descriptive statistics for firm outcomes and outcome-specific firm characteristics for the results reported in Internet Appendix. The number of observations varies by firm-outcome groups because of the different requirements for the number of non-missing observations.

4. Prediction models

We use gradient boosting of regression trees (Freund and Schapire, 1997; Friedman, 2001) to relate corporate governance features and firm characteristics in year t to firm outcomes in year t+1 or t+3.[9] Boosting methods have proved remarkably successful in producing highly accurate out-of-sample predictive performance by combining many relatively inaccurate models such as regression trees (Schapire and Freund, 2012). A regression tree partitions the feature space into a set of regions and uses the mean of the dependent variable as the fitted value for each partition as depicted in Figure 1.[10] For instance, a tree can split the sample by *CEO equity ownership* and use the average operating performance in each region as the estimate. The algorithm can further split these regions by, for instance, *Board tenure*. The second split produces a regression tree with an interaction depth of two because both *CEO equity ownership* and *Board tenure* define a region. This approach estimates a target function by searching in the function space and is shown to provide a consistent estimate when the boosting process is stopped early (Jiang, 2004; Zhang and Yu, 2005; Bartlett and

[9]We use gradient boosting of regression trees as implemented in the `gbm3` R package by Ridgeway (2020).
[10]Strictly speaking, this is the approach that minimizes squared error; other loss functions will yield different estimators, such as the median.

Traskin, 2007).[11]

As discussed in Section 10.7 of Friedman et al. (2009), trees are the best off-the-shelf predictive algorithms because they are fast to construct, interpretable, invariant to strictly monotone transformations of features, and immune to the effects of outliers in features. Regression trees also perform internal feature selection and, as a result, are resistant to the inclusion of irrelevant predictor features. Thus, when we include over a hundred corporate governance features and firm characteristics, the algorithm tends to ignore features that are irrelevant for predicting firm outcomes. However, a single tree is inaccurate and a gradient boosted model often dramatically improves its accuracy while maintaining desirable properties. The boosted tree model is essentially a weighted sum of trees that minimizes a loss function. Each iteration adds a new tree that maximally improves the fit to the data given the already existing model and its fit (Friedman, 2001). This procedure divides the feature space with much higher granularity than a single tree. For firm outcomes captured by indicator variables, we use AdaBoost exponential loss function. For continuous firm outcomes, we use the squared-error loss function, a standard choice for prediction problems with continuous outcomes.

The gradient boosting algorithm depends on three meta-parameters. The first meta-parameter is the interaction depth of the regression trees, which is the number of splits considered for each tree or the highest level of variable interactions allowed.[12] As the optimal value of interaction depth is low in most problems (Friedman et al., 2009), we consider values of 1, 2, 3, 5, and 7, and select the final value for each model using cross-validation.

[11] Experiments and theoretical studies have shown that boosting methods can overfit in the limit of large time or the number of rounds (e.g., Grove and Schuurmans, 1998; Jiang, 2004) and, to achieve consistency, some regularization such as early stopping is necessary.

[12] A value of 1 implies an additive model, a value of 2 implies a model with up to two-way interactions, etc.

The second meta-parameter is the shrinkage or learning rate. This meta-parameter controls the contribution of each new tree that is added to the model, with smaller values reducing over-fitting and thus improving out-of-sample performance (Friedman, 2001). We set the shrinkage parameter to 0.01, which James et al. (2013, p. 323) identifies as a "typical value." The third meta-parameter is the number of trees in the model. There is a trade-off between shrinkage and the optimal number of trees in the model. Smaller values of shrinkage require correspondingly larger values for the number of trees. We set the maximum number of trees to 50,000. Because the algorithm starts with a single tree and grows the model one tree at a time, this means we fit 50,000 trees with various interaction depths and select the final value for the model using cross-validation.

Two parameters—the interaction depth of the regression trees and the number of trees—are chosen by cross-validation in the training data. We set the cross-validation on a rolling basis. For each year t in the training data, we use all the data up to and including year t to estimate the model and then use the following year $t+1$ as the validation set, i.e., apply the estimated model to the data from $t+1$ to compute the prediction error (validation error). For instance, we estimate a model using data from 2001, and then apply the estimated model to the data from 2002 to compute the prediction error. Next, we estimate a model using combined data from 2001 and 2002, and then apply the estimated model to the data from 2003 to compute the prediction error. We continue doing that until the last year in the training sample that is also the last validation year. This process produces average validation errors for each combination of the interaction depth and the number of trees in the model. We then choose the simplest model with an average validation error within 0.001 of the smallest average validation error achieved by models with various numbers of tress and interaction depths. This process favors simpler models with a smaller number of trees and lower interaction depths (e.g., Friedman et al., 2009; Kuhn and Johnson, 2013).

5. Results

After selecting the meta-parameters for each of the models on the training data, we apply these models to each of the three test years from the end of the sample period. The meta-parameters are thus fixed from the training data. However, we still allow the models to learn from the most recent data available for a test year. For instance, data for restatements of financial statements covers the period from 2001 to 2016. We use data from 2001 to 2012 for training and selection of meta-parameters and data from 2013 to 2015 for the out-of-sample test period. For 2013 test data, we re-estimate the model using 2001–2012 data (with meta-parameters from 2001–2012 training data) and apply it to 2013 test data to compute test error. For 2014 test data, we re-estimate the model using 2001–2013 data (again, with meta-parameters from 2001–2012 training data) and apply it to 2014 test data to compute test error. For 2015 test data, we re-estimate the model using 2001–2014 data (again, with meta-parameters from 2001–2012 training data) and apply it to 2015 test data to compute test error. Importantly, the test-year data is *not* used in meta-parameter selection or model re-estimation, and thus allows for a genuine out-of-sample test of the model. For the outcomes measured by the indicator variables, we compute the test error as $\ln(1 + \texttt{AdaBoost error})$. For the outcomes measured by the continuous variables, we compute the test error as RMSE (Root Mean Squared Error). By construction, both errors are positive with lower values corresponding to a better model, i.e., a model with better prediction accuracy. Because general patterns of results are similar for different outcomes, we present the results for three outcomes—serious financial-statement restatements, operating performance, and credit ratings—in the main text of the paper and for the remaining outcomes in Internet Appendix.

5.1 Meta-parameter selection

Table 2 and Table IA.2 in Internet Appendix provide meta-parameters for the gradient boosting machine (GBM) models selected on the training data by the cross-validation procedure in Section 4. We chose the tree depth and the number of trees to minimize cross-validation errors. We consider models that include firm and corporate governance characteristics—both separately and together—to predict future outcomes at $t+1$ and $t+3$.

The following general pattern emerges for all outcomes. The models that combine firm and corporate governance characteristics or that only include corporate governance are generally more complex. They have greater tree depth, i.e., include more complex interaction terms, and have greater number of trees, i.e., include larger number of terms. This increase in model complexity entails greater computational cost, as more complex models take longer to estimate. Among different outcomes, models for S&P credit ratings are the most complex. All models for S&P credit ratings have tree depth of 7, i.e., the highest level we consider is 7-way interaction. The size of the model increases from 5,100 trees for firm characteristics, to 20,650 trees for firm and corporate governance characteristics, and to 40,850 for corporate governance alone.

However, this increase in complexity does not come with substantial reduction in cross-validation errors. While adding corporate governance to the firm-characteristics-only models does often reduce the cross-validation errors, this reduction is not substantial. By contrast, having corporate governance on its own, again, results in more complex but *less* accurate models. For instance, for return on assets, the tree depth is 3, i.e., allows for 3-way interactions, and the size of the model is 1,050 producing an error of 0.086 for firm characteristics; the tree depth is 3 and the size of the model is 1,380 producing the same error of 0.086 for firm and corporate governance characteristics combined; and the tree depth is 7 and the size of the model is 42,700 producing the larger error of 0.138 for corporate governance alone. The greater complexity of corporate-governance-only models and the lack of substantial improvement in cross-validation errors suggests that GBM has difficulty extracting informative signals about outcomes from these variables. This may be because corporate governance is not as informative about outcomes as firm characteristics, which weighs against a strong causal effect of corporate governance.

5.2 Out-of-sample predictive performance

Out-of-sample errors are reported separately for each test year in sub-panels of Tables 3–8 and Tables IA.3–IA.14 in Internet Appendix. We also report t-statistics values that test for statistically significant differences in errors for each test year. With t-statistics, we compare the model in the column to the model in the corresponding row. That is, the value is positive when the model in the column is more accurate than the model in the corresponding row, i.e., has *lower* error; the value is negative when the model in the column is less accurate than the model in the corresponding row, i.e., has *higher* error. *Base model* denotes an uninformed baseline that uses an average outcome in the estimation data for prediction.

For each outcome, there are two tables. The first table contrasts errors from models that include firm characteristics alone and firm characteristics combined with corporate governance. The second table contrasts errors from models that include firm characteristics and corporate governance on their own. Out-of-sample prediction errors for more serious financial-statement restatements are in Tables 3–4, for operating performance in Tables 5–6, and for credit ratings in Tables 7–8. In Internet Appendix, out-of-sample prediction errors for the broader definition of financial-statement restatements are in Tables IA.3–IA.4, for class-action lawsuits in Tables IA.5–IA.6, for business failures in Tables IA.7–IA.8, for firm value in Tables IA.9–IA.10, for stock returns in Tables IA.11–IA.12, and for investment-grade debt in Tables IA.13–IA.14. All of the firm outcomes for year t are computed as leads $t + 1$ and $t + 3$. Considering a longer horizon $t + 3$ allows us to capture the possibility of a long-term effect of governance variables.

The following general pattern emerges. Models based on firm characteristics alone outperform base models. The exception is stock returns for which none of the models outperform the base model. Although adding corporate governance leads to a reduction in errors, this reduction is not statistically significant. Thus, adding corporate governance to the firm-characteristics-only models does not improve prediction accuracy. A similar pattern emerges when considering firm and corporate governance characteristics on their own. Corporate-governance-only models do not perform better than base models with two exceptions of compensation and board characteristics and, typically, have larger errors. Compensation and board characteristics often outperform base models but do not deliver accuracy that is statistically different from the accuracy of firm-characteristics-only models, e.g., financial restatement events, class-action lawsuits, business failures, or deliver performance that is statistically inferior to the firm-characteristics-only models, e.g., operating performance, firm value, having an investment grade debt, and S&P credit rating.

The two outcomes that deviate from the general pattern in a meaningful way are S&P credit rating in Tables 7–8 and having an investment grade debt in Tables IA.13–IA.14 in Internet Appendix. For S&P credit ratings, adding compensation or board characteristics improves the accuracy over firm-characteristics-only models in Table 7. As for Table 8, while the accuracy of corporate-governance-only models outperforms base models for *all* corporate governance groups, these models are statistically inferior to firm-characteristics-only models. Both of the outcomes come from S&P credit ratings data and, hence, these accuracy patterns may simply capture properties of S&P's credit-rating methodology. Indeed, S&P discloses that it evaluates management and governance of a firm as part of its credit rating process, and our machine learning models may simply recover this from the data.[13]

We identify two extreme possibilities to frame our results in possibly causal terms. First, only firm characteristics (X_1) drive firm outcomes (Y), while corporate governance characteristics (X_2) are irrelevant and have no effect. Second, X_1 fully mediates the effect of X_2 on Y. If X_1 and X_2 are capturing the same information about Y, we should see similar accuracy for the models that include X_1 and X_2 on their own, which is not the case. Instead, the two patterns are: (1) X_1-only models outperform base models but X_2-only models perform similarly to base models, e.g., financial restatement events, class-action lawsuits, business failures and (2) X_2-only models outperform base models but

[13]See S&P Global Ratings disclosures "Criteria | Corporates | General: Corporate Methodology" and "General Criteria: Methodology: Management And Governance Credit Factors For Corporate Entities General Criteria: Methodology: Management And Governance Credit Factors For Corporate Entities".

underperform X_1-only models, e.g., operating performance, firm value, having investment grade debt, and S&P credit rating.

Based on this evidence, while we cannot say that corporate governance characteristics X_2 are irrelevant, omitting them in predictive models produces no substantial loss of prediction accuracy. In contrast, omitting firm characteristics X_1 triggers a substantial accuracy loss. Because we find little evidence for X_1 and X_2 providing the same information about Y, according to Section 2, the more likely interpretation of our results is that the corporate governance features we consider collectively have a trivial causal effect relative to firm characteristics, if any. Predictable variation in firm outcomes is mainly captured by firm characteristics.

5.3 Variable importance

Figures 2–4 and Figures IA.1–IA.6 in Internet Appendix show the characteristics that matter most for predicting firm outcomes in the models that include firm and all corporate governance variables. We compute the relative importance of various characteristics as the reduction of the error attributable to this predictor as described in Friedman (2001). There is a mix of firm and corporate governance characteristics among the top predictors for some outcomes, e.g., financial restatement events, class-action lawsuits, stock returns. For other outcomes, top predictors comprise of firm characteristics alone, e.g., business failures, return on assets, firm value, having investment grade debt, S&P credit rating.

The most important variables align well with the extant literature. For financial restatement events, having financial experts on the board and executive compensation matters (e.g., Cohen et al., 2014; Armstrong et al., 2010). For class-action lawsuits, the most important predictors are industry and size (e.g., Rogers and Stocken, 2005). For business failures, the most important predictors are stock price and excess stock return (e.g., Campbell et al., 2008). For return on assets and firm value, the most important predictor is their lagged values (e.g., Larcker et al., 2007). Interestingly, for stock returns, growth in CEO equity holdings is the most important predictor followed by book-to-market ratio. However, these models do not outperform the uninformed baseline out-of-sample. For credit-rating outcomes, industry and size are the most important predictors (e.g., Daines et al., 2010).

We also aggregate variable importance by firm and corporate governance groups. For all outcomes except for stock returns, firm characteristics is the most important group of predictors. It is often followed by compensation as the second tangibly relevant group of predictors, which is consistent with a large literature on the importance of compensation incentives (e.g., Edmans et al., 2017). These relative importance rankings corroborate in-sample and out-of-sample results that firm characteristics contain the most predictive variation for firm outcomes.

5.4 Alternative timing for the train-test split

Our main analyses uses the data in the beginning of the sample to train the models and the end of the sample to test them over 2001–2016 period. This period includes the 2007–2008 financial crisis and the Dodd–Frank Wall Street Reform and Consumer Protection Act, commonly referred to as Dodd–Frank, enacted on July 21, 2010. Here, we consider three alternative time periods for the train-test split. The period before the financial crisis, that is, training data covers 2001–2004 and test data uses 2005 with $t + 1$ outcomes from 2006 not being contaminated by 2007 events related to the 2007–2008 financial crisis. The period after the Dodd-Frank Act, that is, training data covers 2011–2014 and test data uses 2015 with $t + 1$ outcomes from 2016. The reverse timing for the train-test split, that is, we use 2001–2003 as the test data and 2004–2016 as the training data.

Tables IA.15–IA.32 in Internet Appendix report the out-of-sample performance for $t+1$ outcomes for these alternative specifications. The out-of-sample performance comparisons are similar to our main results and the main conclusion applies: firm characteristics capture most of the predictive variation with corporate governance characteristics, even when better than the base model, performing similar or substantially worse on their own. We also find deterioration of performance for firm-characteristics-based models for some outcomes. For business failures, firm-characteristics-based models do not outperform the base model in the pre-financial crisis period in Tables IA.21–IA.22. For financial restatements, firm-characteristics-based models do not outperform the base model in the post-Dodd-Frank and 2001-2003 periods in Tables IA.34–IA.36 and IA.52–IA.54. Both of these outcomes are rare, and thus harder to predict, which results in the performance of firm-characteristics-based models been sensitive to the length and timing of the training period.

6. Re-examination of Duchin et al. (2010)

While many papers have focused on associations between governance variables and firm outcomes, ascribing causal explanations to these has not gone without criticism. A particular concern is the endogeneity of governance choices by firms (Hermalin and Weisbach, 2003). To address concerns about the endogenous selection of governance variables, researchers have used various strategies to identify variation in corporate governance features that are plausibly random (or "as if" random) to draw more credible causal inferences (Dunning, 2012).

To illustrate how our basic approach can be applied in such settings, we re-examine the setting of Duchin et al. (2010) ("DMO"), which studies the effects of independent directors on various measures of firm performance. Acknowledging that board composition is endogenous, DMO focus on instrumental variable regressions in their analysis. An instrumental variable is a variable that is unconfounded (i.e., random or "as if" random), is *a priori* known almost certainly to have a causal effect on the treatment of interest, and that satisfies the exclusion restriction, which requires that any causal effect of the instrument "passes through" the treatment of interest (Imbens and Rubin, 2015, pp. 514-515).

In evaluating the impact of independent directors on subsequent firm performance, DMO use compliance with the requirements of Sarbanes-Oxley Act of 2002 (SOX) prior to the enactment of SOX as an instrument for changes in board composition once SOX came into effect. DMO predict—and test for—differential effects of independent directors for firms based on differences in measures of the cost to outsiders of acquiring information about the firm ("information cost"). Consistent with their predictions, DMO find that independent directors increase firm performance—measured using changes in operating performance, changes in Tobin's Q, and stock returns—when information cost is low, but decrease firm performance when information cost is high.

We adapt and apply our machine-learning approach to the setting of DMO. Applying the same gradient boosting machine (GBM) approach used elsewhere in this paper, we examine whether the instrument used by DMO can be used to predict the firm outcomes studied in DMO incremental to the control variables included by DMO.

We focus on this "intention-to-treat" (ITT) analysis for a number of reasons. First, the *magnitude* of the causal effect is not the focus of our analysis, merely whether evidence of a causal effect can be observed in prediction models. Second, because the ITT is an essential element of the estimated effect (Angrist and Pischke, 2008, pp. 162-5), evidence of the existence (or absence) of ITT effects has strong probative value for the existence of causal effects of the kind postulated by DMO. Finally, ITT analysis is much more easily incorporated into our machine-learning based approach, especially as it facilitates robust statistical inference in that setting, as discussed below.

Because credible identification strategies need to be carefully constructed by a research team for a given research setting, we follow the research choices made by Duchin et al. (2010) to the greatest extent possible modulo our use of machine-learning models in place of the conventional instrumental variable analysis used by Duchin et al. (2010).[14] We use the same data, the same instrument, include the same exogenous variables as controls, and the same outcome variables.[15]

Before conducting our machine-learning analysis, we first confirm that we can replicate the IV analysis of DMO as reported in Table 2 of Atanasov and Black (2021).[16] Table 9 shows that we can exactly replicate the regression coefficients reported in Table 2 of Atanasov and

[14]It is important to note that Atanasov and Black (2021) find evidence of severe covariate imbalance across the two values of the Duchin et al. (2010) instrument. This suggests that the instrument is neither random nor "as if" random undermining its value as an instrument. While Atanasov and Black (2021) attempt to remedy the failure of randomization by using matching analyses, these will not deliver consistent estimates of causal effects if there are unobservable confounders of precisely the kind leading to the use of IV analysis in the first place. As such, we do not consider the modified approach of Atanasov and Black (2021) and view our analysis as merely indicative of how machine-learning approach can be applied in setting where credible identification strategies can be found.

[15]We thank the authors of Duchin et al. (2010) for allowing us to use their data and thank the authors of Atanasov and Black (2021) for sharing their code and the Duchin et al. (2010) data with us.

[16]We use the analysis of Atanasov and Black (2021) because this addresses "two technical errors" acknowledged by the authors of Duchin et al. (2010). See the supplementary materials for Atanasov and Black (2021) for discussion of the details.

Black (2021).

We then conduct ITT or "reduced form" versions of the DMO analyses in which we use the first-stage instruments in the second stage and omit the endogenous regressors. Table 10 presents the results of these ITT versions of the regressions reported in columns (3), (4), and (5) of Table 9. We see that the results reported in Duchin et al. (2010) and in Table 9 have close analogues in intention-to-treat analysis. The coefficients on the *Noncomply dummy* are positive in all three regressions, consistent with the positive coefficients on *Instrumented* Δ *Indep* reported in Table 9. The coefficients on the *Noncomply dummy* $\times$ *InfoCost* are negative in all three regressions, consistent with the negative coefficients on *Instrumented* (Δ *Indep* $\times$ *InfoCost)* reported in Table 9.

In addition to following the research choices made by Duchin et al. (2010), we depart from our main analysis in two respects. First, because of the small sample size for this analysis, we use 10-fold cross-validation analysis in place of a hold-out test sample, as used in our main analysis. Kuhn and Johnson (2013, p. 77-78) say "there is a strong technical case to be made against a single, independent test set" and "if the samples size is small, we recommend repeated 10-fold cross-validation for several reasons: the bias and variance properties are good and, given the sample size, the computational costs are not large." The risk with using cross-validation in place of a holdout sample is one of overstating the true out-of-sample performance of the model, but the results of our analysis suggest this is not a concern.

Second, we use a model that includes just industry dummies as our baseline model. The DMO analysis includes 48 Fama-French industry dummies and we include industry dummies in the feature set to maintain the parallel. However, a complication in our analysis is that we need to make sure that data on all industries are available in all folds. To ensure this, we aggregate firms in Fama-French 48-industry groups with fewer than 10 observations into a single "other" industry.

Cross-validation MSEs for the fitted models for each of three different outcomes considered in DMO are presented in Table 11. The *Base MSE* column presents MSEs from the baseline model. The *MSE without IV* column presents MSEs from applying GBM with just the controls from DMO (including the industry dummies and the information index) *without* the exogenous instrument, *Noncomply dummy*. The *MSE with IV* column presents MSEs from applying GBM with both the controls from DMO *and* the exogenous instrument, *Noncomply dummy*. The *MSE decrease* column presents the difference between the value in *MSE without IV* column and that in the *MSE with IV* column. The *p-value* column presents p-values derived using randomization inference. Because the exogenous instrument is random (or "as if" random), we can evaluate the distribution of *MSE decrease* under the null hypothesis by randomly reshuffling the *Noncomply dummy* and running the GBM model with the resulting data. Doing this 999 times gives us an empirical distribution of *MSE decrease* generated under the null hypothesis. Adding the observed value of *MSE decrease* to these allows us to measure the p-value to three decimal places. Because we predict a positive value in *MSE decrease*, we use a one-sided p-value in this column. In the context of instrumental variables, randomization inference offers a number of benefits compared to more conventional statistical tests based on asymptotic properties of estimators. First, randomization inference does not suffer from the well-known problems with inference when using weak instruments (Bound et al., 1995; Imbens and Rosenbaum, 2005). In the context of randomization inference using instruments, Rosenbaum (2020, p. 153) points out that "the intention-to-treat analysis will reject Fisher's hypothesis of no treatment effect if and only if the instrumental variable (IV) analysis rejects $H_0 : \beta = 0$." With p-values of 0.200, 0.632, and 0.502 for $\Delta \ln(Q)$, ΔROA, and *Mean return*, respectively, we do not find evidence that exogenous shocks to board independence predict firm performance.

7. Conclusion

In this paper, we use machine learning to re-examine the broad research questions of measurement, prediction, and causation in corporate governance. We evaluate predictive ability of over a hundred corporate governance characteristics for important firm outcomes. We discover that adding corporate governance does not improve the models' predictive accuracy beyond the predictive accuracy captured by firm characteristics. While the models become more complex, firm characteristics still dominate in terms of their relative importance for prediction.

Our paper contributes to the literature examining the predictive ability of corporate governance measures, providing additional evidence on the difficulty of constructing meaningful and useful measures of corporate governance documented by Larcker et al. (2007) and Daines et al. (2010). Our results suggest that these findings generalize beyond the specific governance measures that those papers study.

We tentatively suggest that the failure of corporate governance measures to predict the kinds of outcomes studied in prior research may have implications for the existence and magnitude of causal effects of corporate governance on firm outcomes. Some predictive ability is a necessary condition for a causal effect to exist (Freedman, 1991; Manski, 2009;

Watts, 2014).

While underspecified models can predict better than fully specified causal models (Hagerty and Srinivasan, 1991; Wu et al., 2007), it seems unlikely that an underspecified model with better predictive ability would omit *all* of the (causal) corporate governance features as our models generally do, suggesting that such a fully specified model is unlikely.

Our results seem consistent with corporate governance theories offering little in terms of explanatory power for firm outcomes. Perhaps further work is needed to develop models and measures with greater predictive power. Alternatively, it may be that the effects of corporate governance on firm outcomes, if any, are too small to be detected even in large samples.

References

Adams, R. B., 2017. Boards, and the directors who sit on them. In: *The Handbook of the Economics of Corporate Governance*, Elsevier, vol. 1, pp. 291–382.

Agrawal, A., Knoeber, C. R., 1996. Firm performance and mechanisms to control agency problems between managers and shareholders. Journal of Financial and Quantitative Analysis 31, 377–397.

Agrawal, M., Peterson, J. C., Griffiths, T. L., 2020. Scaling up psychology via scientific regret minimization. Proceedings of the National Academy of Sciences 117, 8825–8835.

Amihud, Y., Schmid, M., Davidoff Solomon, S., 2017. Do staggered boards affect firm value? Available at SSRN 2948141 .

Amihud, Y., Stoyanov, S., 2017. Do staggered boards harm shareholders? Journal of Financial Economics 123, 432–439.

Angrist, J. D., Pischke, J.-S., 2008. Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University Press.

Armstrong, C. S., Jagolinzer, A. D., Larcker, D. F., 2010. Chief executive officer equity incentives and accounting irregularities. Journal of Accounting Research 48, 225–271.

Ashbaugh-Skaife, H., Collins, D. W., LaFond, R., 2006. The effects of corporate governance on firms' credit ratings. Journal of Accounting and Economics 42, 203–243.

Atanasov, V., Black, B., 2021. The trouble with instruments: The need for pretreatment balance in shock-based instrumental variable designs. Management Science 67, 1270–1302.

Avedian, A., Cronqvist, H., Weidenmier, M., 2015. Corporate governance and the creation of the SEC. Swedish House of Finance Research Paper .

Baliga, B. R., Moyer, R. C., Rao, R. S., 1996. CEO duality and firm performance: What's the fuss? Strategic Management Journal 17, 41–53.

Bartlett, P. L., Traskin, M., 2007. AdaBoost is consistent. Journal of Machine Learning Research 8, 2347–2368.

Bebchuk, L., Cohen, A., Ferrell, A., 2009. What matters in corporate governance? Review of Financial Studies 22, 783–827.

Bhagat, S., Black, B., 2001. The non-correlation between board independence and long-term firm performance. Journal of Corporation Law 27, 231.

Bhojraj, S., Sengupta, P., 2003. Effect of corporate governance on bond ratings and yields: The role of institutional investors and outside directors. Journal of Business 76, 455–475.

Bound, J., Jaeger, D. A., Baker, R. M., 1995. Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. Journal of the American Statistical Association 90, 443–450.

Boyd, B. K., 1995. CEO duality and firm performance: A contingency model. Strategic Management Journal 16, 301–312.

Brickley, J. A., Coles, J. L., Jarrell, G., 1997. Leadership structure: Separating the CEO and chairman of the board. Journal of Corporate Finance 3, 189–220.

Campbell, J. Y., Hilscher, J., Szilagyi, J., 2008. In search of distress risk. Journal of Finance 63, 2899–2939.

Cheffers, M., Usvyatsky, O., Pakaluk, J., 2014. Identifying accounting irregularities using Audit Analytics databases. Research report, Audit Analytics .

Cohen, A., Wang, C. C., 2013. How do staggered boards affect shareholder value? Evidence from a natural experiment. Journal of Financial Economics 110, 627–641.

Cohen, A., Wang, C. C., 2017. Reexamining staggered boards and shareholder value. Journal of Financial Economics 125, 637–647.

Cohen, J. R., Hoitash, U., Krishnamoorthy, G., Wright, A. M., 2014. The effect of audit committee industry expertise on monitoring the financial reporting process. The Accounting Review 89, 243–273.

Cohen, L., Frazzini, A., Malloy, C. J., 2012. Hiring cheerleaders: Board appointments of “independent” directors. Management Science 58, 1039–1058.

Coles, J. L., Daniel, N. D., Naveen, L., 2014. Co-opted boards. Review of Financial Studies 27, 1751–1796.

Cremers, K. M., Litov, L. P., Sepe, S. M., 2017. Staggered boards and long-term firm value, revisited. Journal of Financial Economics 126, 422–444.

Daines, R., Li, S. X., Wang, C. C., 2021. Can staggered boards improve value? Causal evidence from Massachusetts. Contemporary Accounting Research 38, 3053–3084.

Daines, R. M., Gow, I. D., Larcker, D. F., 2010. Rating the ratings: How good are commercial governance ratings? Journal of Financial Economics 98, 439–461.

Dalton, D. R., Daily, C. M., Ellstrand, A. E., Johnson, J. L., 1998. Meta-analytic reviews of board composition, leadership structure, and financial performance. Strategic Management Journal 19, 269–290.

Dechow, P. M., Ge, W., Larson, C. R., Sloan, R. G., 2011. Predicting material accounting misstatements. Contemporary Accounting Research 28, 17–82.

Dey, A., Engel, E., Liu, X., 2011. CEO and board chair roles: To split or not to split? Journal of Corporate Finance 17, 1595–1618.

Duchin, R., Matsusaka, J. G., Ozbas, O., 2010. When are outside directors effective? Journal of Financial Economics 96, 195–214.

Dunning, T., 2012. Natural Experiments in the Social Sciences: A Design-Based Approach. Cambridge University Press.

Edmans, A., Gabaix, X., Jenter, D., 2017. Executive compensation: A survey of theory and evidence. The Handbook of the Economics of Corporate Governance 1, 383–539.

Faleye, O., 2007. Classified boards, firm value, and managerial entrenchment. Journal of Financial Economics 83, 501–529.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1–22.

Fracassi, C., Tate, G., 2012. External networking and internal firm governance. Journal of Finance 67, 153–194.

Francis, B. B., Hasan, I., Wu, Q., 2012. Do corporate boards matter during the current financial crisis? Review of Financial Economics 21, 39–52.

Freedman, D. A., 1991. Statistical models and shoe leather. Sociological Methodology pp. 291–313.

Freund, Y., Schapire, R. E., 1997. A decision-theoretic generalization of on-line learning and an application to boosting. Journal of Computer and System Sciences 55, 119–139.

Friedman, J., Hastie, T., Tibshirani, R., 2009. The elements of statistical learning: Data mining, inference, and prediction. New York, NY: Springer-Verlag New York.

Friedman, J. H., 2001. Greedy function approximation: A gradient boosting machine. Annals of Statistics pp. 1189–1232.

Fudenberg, D., Kleinberg, J., Liang, A., Mullainathan, S., 2022. Measuring the completeness of economic models. Journal of Political Economy 130, 956–990.

Ge, W., Tanlu, L., Zhang, J. L., 2016. What are the consequences of board destaggering? Review of Accounting Studies 21, 808–858.

Goergen, M., Limbach, P., Scholz-Daneshgari, M., 2020. Firms' rationales for CEO duality: Evidence from a mandatory disclosure regulation. Journal of Corporate Finance 65, 101770.

Gompers, P., Ishii, J., Metrick, A., 2003. Corporate governance and equity prices. Quarterly Journal of Economics 118, 107–156.

Gow, I. D., Larcker, D. F., Reiss, P. C., 2016. Causal inference in accounting research. Journal of Accounting Research 54, 477–523.

Grove, A. J., Schuurmans, D., 1998. Boosting in the limit: Maximizing the margin of learned ensembles. In: *AAAI/IAAI*, pp. 692–699.

Guo, R.-J., Kruse, T. A., Nohel, T., 2008. Undoing the powerful anti-takeover force of staggered boards. Journal of Corporate Finance 14, 274–288.

Hagerty, M. R., Srinivasan, V., 1991. Comparing the predictive powers of alternative multiple regression models. Psychometrika 56, 77–85.

Harvey, C. R., 2017. Presidential address: The scientific outlook in financial economics. The Journal of Finance 72, 1399–1440.

Hempel, C. G., Oppenheim, P., 1948. Studies in the logic of explanation. Philosophy of Science 15, 135–175.

Hennes, K. M., Leone, A. J., Miller, B. P., 2008. The importance of distinguishing errors from irregularities in restatement research: The case of restatements and CEO/CFO turnover. The Accounting Review 83, 1487–1519.

Hermalin, B., Weisbach, M., 2003. Boards of directors as an endogenously determined institution: A survey of the economic literature. Economic Policy Review 9, 7–26.

Hermalin, B. E., Weisbach, M. S., 1991. The effects of board composition and direct incentives on firm performance. Financial Management pp. 101–112.

Hofman, J. M., Watts, D. J., Athey, S., Garip, F., Griffiths, T. L., Kleinberg, J., Margetts, H., Mullainathan, S., Salganik, M. J., Vazire, S., et al., 2021. Integrating explanation and prediction in computational social science. Nature 595, 181–188.

Hwang, B.-H., Kim, S., 2009. It pays to have friends. Journal of Financial Economics 93, 138–158.

Imbens, G. W., Rosenbaum, P. R., 2005. Robust, accurate confidence intervals with a weak instrument: quarter of birth and education. Journal of the Royal Statistical Society: Series A (Statistics in Society) 168, 109–126.

Imbens, G. W., Rubin, D. B., 2015. Causal Inference for Statistics, Social and Biomedical Sciences: An Introduction. Cambridge University Press.

Ioannidis, J. P. A., 2005. Why most published research findings are false. PLoS Medicine 2, e124.

James, G., Witten, D., Hastie, T., Tibshirani, R., 2013. An Introduction to Statistical Learning with Applications in R. Springer Texts in Statistics, Spring-Verlag, New York.

Jiang, W., 2004. Process consistency for AdaBoost. Annals of Statistics 32, 13–29.

Klein, A., 1998. Firm performance and board committee structure. Journal of Law and Economics 41, 275–304.

Knyazeva, A., Knyazeva, D., Masulis, R. W., 2013. The supply of corporate directors and board independence. Review of Financial Studies 26, 1561–1605.

Krause, R., Semadeni, M., Cannella Jr, A. A., 2014. CEO duality: A review and research agenda. Journal of Management 40, 256–286.

Kuhn, M., Johnson, K., 2013. Applied Predictive Modeling. SpringerLink : Bücher, Springer New York.

Larcker, D., Tayan, B., 2015. Corporate governance matters: A closer look at organizational choices and their consequences. Pearson education.

Larcker, D. F., Ormazabal, G., Taylor, D. J., 2011. The market reaction to corporate governance regulation. Journal of Financial Economics 101, 431–448.

Larcker, D. F., Richardson, S. A., Tuna, I., 2007. Corporate governance, accounting outcomes, and organizational performance. The Accounting Review 82, 963–1008.

Larcker, D. F., Tayan, B., 2016. Chairman and CEO: The controversy over board leadership structure. Rock Center for Corporate Governance at Stanford University Closer Look Series: Topics, Issues and Controversies in Corporate Governance No. CGRP-58, Stanford University Graduate School of Business Research Paper .

Manski, C. F., 2009. Identification for prediction and decision. Harvard University Press.

Nguyen, B. D., 2012. Does the rolodex matter? Corporate elite's small world and the effectiveness of boards of directors. Management Science 58, 236–252.

Nguyen, B. D., Nielsen, K. M., 2010. The value of independent directors: Evidence from sudden deaths. Journal of Financial Economics 98, 550–567.

Ogneva, M., Piotroski, J. D., Zakolyukina, A. A., 2020. Accounting fundamentals and systematic risk: Corporate failure over the business cycle. The Accounting Review 95, 321–350.

Peysakhovich, A., Naecker, J., 2017. Using methods from machine learning to evaluate behavioral models of choice under risk and ambiguity. Journal of Economic Behavior & Organization 133, 373–384.

Richardson, S. A., Sloan, R. G., Soliman, M. T., Tuna, I., 2005. Accrual reliability, earnings persistence and stock prices. Journal of Accounting and Economics 39, 437–485.

Ridgeway, G., 2020. gbm: Generalized Boosted Regression Models. R package version 2.1.8.

Rogers, J. L., Stocken, P. C., 2005. Credibility of management forecasts. The Accounting Review 80, 1233–1260.

Rosenbaum, P. R., 2020. Design of Observational Studies. Springer International Publishing, second ed.

Rosenstein, S., Wyatt, J. G., 1990. Outside directors, board independence, and shareholder wealth. Journal of Financial Economics 26, 175–191.

Schapire, R., Freund, Y., 2012. Boosting: Foundations and Algorithms. MIT Press.

Shmueli, G., 2010. To explain or to predict? Statistical Science 25, 289–310.

Terry, S. J., Whited, T. M., Zakolyukina, A. A., 2022. Information versus investment. The Review of Financial Studies Hhac052.

Watts, D. J., 2014. Common sense and sociological explanations. American Journal of Sociology 120, 313–351.

Wu, S., Harris, T., McAuley, K., 2007. The use of simplified or misspecified models: Linear case. The Canadian Journal of Chemical Engineering 85, 386–398.

Yarkoni, T., Westfall, J., 2017. Choosing prediction over explanation in psychology: Lessons from machine learning. Perspectives on Psychological Science 12, 1100–1122.

Zakolyukina, A. A., 2018. How common are intentional GAAP violations? Estimates from a dynamic model. Journal of Accounting Research 56, 5–44.

Zhang, T., Yu, B., 2005. Boosting with early stopping: Convergence and consistency. Annals of Statistics 33, 1538–1579.

Table A.1: **Variable definitions**

Panel A: Corporate governance: Institutional investor holdings

Variable	Definition
Instit. ownership	Company's common stock held by institutional investors (%)
Instit. ownership., top 5	Company's common stock held by the five largest institutional investors (%)
Blockholder	Percent of company's stock held by institutions owning 5% or more

Panel B: Corporate governance: Anti-takeover provisions

Variable	Definition
PA, OH, WI, MA incorporated	An indicator for the firm being incorporated in Pennsylvania, Ohio, Wisconsin, or Massachusetts
Staggered board	An indicator variable for the firm having a staggered board
Unequal voting rights	An indicator variable for the unequal voting rights across common shareholders
Poison pill	An indicator variable for the firm having adopted a poison pill (in effect)
Supermajority to amend charter	An indicator variable for the firm having a supermajority provision to amend charter
Supermajority to approve mergers	An indicator variable for the firm having a supermajority provision to approve mergers
Supermajority to amend bylaws	An indicator variable for the firm having a supermajority provision to amend bylaws

Panel C: Corporate governance: Executive compensation

Variable	Definition
Shares held (%), CEO	Percent of common shares held by the CEO
Total shares held (%), exec.	Percent of common shares held by non-CEO executives
Avg. shares held (%), exec.	Average non-CEO executive share ownership
Var. shares held (%), exec.	Variance of non-CEO executive share ownership
Comp-type, CEO	Compensation-type received by the CEO (see comp-type below)
Avg. comp-type, exec.	Average compensation-type received by non-CEO executives (see comp-type below)
Var. comp-type, exec.	Variance of compensation-type received by non-CEO executives (see comp-type below)
Comp-type, exec., ratio	Log-ratio of CEO to non-CEO executives compensation-type (see comp-type below)
Comp-type: Stock awards	Restricted stock awards (number of shares in millions)
Comp-type: Cash compensation	Total cash compensation
Comp-type: Value option grants	Black-Scholes value of new option grants
Comp-type: Value vested options	Black-Scholes value of vested unexercised options
Comp-type: Value non-vested options	Black-Scholes value of non-vested options
Comp-type: Value shares held	Value of shares held
Comp-type: Delta option grants	Black-Scholes delta of new option grants

Table A.1: —*Continued*

Variable	Definition
Comp-type: Delta vested options	Black-Scholes delta of vested unexercised options
Comp-type: Delta non-vested options	Black-Scholes delta of non-vested options
Comp-type: Delta shares held	Delta of shares held (i.e., the number of shares held)
Comp-type: Vega option grants	Black-Scholes vega of new option grants
Comp-type: Vega vested options	Black-Scholes vega of vested unexercised options
Comp-type: Vega non-vested options	Black-Scholes vega of non-vested options
Comp-type: Value all equity	Black-Scholes value of all equity held
Comp-type: Delta all equity	Black-Scholes delta of all equity held
Comp-type: Vega all equity	Black-Scholes vega of all equity held
Comp-type: Value vested equity	Black-Scholes value of all vested equity
Comp-type: Delta vested equity	Black-Scholes delta of all vested equity
Comp-type: Vega vested equity	Black-Scholes vega of all vested equity
Comp-type: Value all equity log-growth	Log-growth of Black-Scholes value of all equity
Comp-type: Delta all equity log-growth	Log-growth of Black-Scholes delta of all equity
Comp-type: Vega all equity log-growth	Log-growth of Black-Scholes vega of all equity
Panel D: Corporate governance: Board's financial expertise	
Variable	Definition
Num. financial experts	Number of financial experts on the board
Financial experts (%)	Percent of financial experts on the board
Num. audit insiders	Number of insider directors on the audit committee
Audit insiders (%)	Percent of insider directors on the audit committee
Num. finance insiders	Number of insider directors on the finance committee
Finance insiders (%)	Percent of insider directors on the finance committee
Num. audit directors	Number of directors on the audit committee
Audit directors (%)	Percent of directors on the audit committee
Num. finance directors	Number of directors on the finance committee
Finance directors (%)	Percent of directors on the finance committee
Panel E: Corporate governance: Board characteristics	
Variable	Definition
Num. post-CEO directors	Number of directors who joined the board after CEO was appointed
Post-CEO directors (%)	Percent of directors who joined the board after CEO was appointed

Table A.1: —*Continued*

Variable	Definition
Num. over 69 directors	Number of directors who are older than 69 years old
Over 69 directors (%)	Percent of directors who are older than 69 years old
Avg. director age	Average director age
Num. busy directors	Number of directors who are busy (on at least three boards)
Busy directors (%)	Percent of directors who are busy (on at least three boards)
Num. directors	Number of directors on the board
CEO Chairman of the board	An indicator variable for CEO also holding the title of the Chairman of the board
Num. CEO directors	Number of directors who are also CEOs of another firm
CEO directors (%)	Percent of directors who are also CEOs of another firm
Num. outsider directors	Number of directors who are not also officers of the firm
Outsider directors (%)	Percent of directors who are not also officers of the firm
Num. insider directors	Number of directors who are also officers of the firm
Insider directors (%)	Percent of directors who are also officers of the firm
Num. affiliate directors	Number of directors who are affiliated
Affiliate directors (%)	Percent of directors who are affiliated
Board tenure	The average tenure of outsider directors
Female directors (%)	Percent of female directors
Total equity, director	Total equity owned by directors
Avg. equity, director	Average equity owned by directors
Var. equity, director	Variance of equity owned by directors
Num. nomination insiders	Number of insider directors on the nomination committee
Nomination insiders (%)	Percent of insider directors on the nomination committee
Num. compensation insiders	Number of insider directors on the compensation committee
Compensation insiders (%)	Percent of insider directors on the compensation committee
Num. compliance insiders	Number of insider directors on the compliance committee
Compliance insiders (%)	Percent of insider directors on the compliance committee
Num. governance insiders	Number of insider directors on the governance committee
Governance insiders (%)	Percent of insider directors on the governance committee
Num. nomination directors	Number of directors on the nomination committee
Nomination directors (%)	Percent of directors on the nomination committee
Num. compensation directors	Number of directors on the compensation committee
Compensation directors (%)	Percent of directors on the compensation committee
Num. compliance directors	Number of directors on the compliance committee

Table A.1: —*Continued*

Variable	Definition
Compliance directors (%)	Percent of directors on the compliance committee
Num. governance directors	Number of directors on the governance committee
Governance directors (%)	Percent of directors on the governance committee
Avg. value shares held, director	Average value of shares held by directors
Var. value shares held, director	Variance of value of shares held by directors
Value shares held, director, ratio	Log-ratio of CEO to director value of shares held
	Panel F: Outcome group: Restatements of financial statements
Variable	Definition
Restatements as in Hennes et al. (2008)	An indicator variable for more serious financial-statement restatements as defined in Terry et al. (2022) that incorporate criteria from Hennes et al. (2008)
Restatement events	An indicator variable for the broad category of financial-statement restatement events as defined in Terry et al. (2022)
RSST accruals	Accruals following Richardson et al. (2005) divided by average total assets (AT)
Receivables growth	Change in receivable (RECT) divided by average total assets (AT)
Inventory growth	Change in inventory (INVT) divided by average total assets (AT)
Soft assets	(Total Assets (AT) - PP&E (PPENT) - Cash and Cash Equivalent (CHE))/Total Assets (AT)
Cash sales growth	Change in cash sales [Sales (SALE) - Change Accounts Receivable (RECT)] divided by average total assets (AT)
Return on assets, growth	One-year growth in return on assets
Issuance	An indicator variable for actual issuance, that is, sale of common and preferred stock or long-term debt issuance greater than zero
	Panel G: Outcome group: Class-action lawsuits
Variable	Definition
Class-action lawsuits	An indicator variable for the fiscal year overlapping with a class-action period
Size, log	Log of the average market value of equity measured in dollars
Turnover	Average daily trading volume divided by the average shares outstanding
Beta	Slope from regressing daily returns on CRSP value-weighted index
Stock returns, 12-month	Stock returns over 12 months
Volatility, 12-month	Standard deviation of daily returns over 12 months
Daily returns, skewness	Skewness of daily returns
Min. daily returns	Minimum of the daily returns

Table A.1: —*Continued*

Variable	Definition
Bio-technology industry	An indicator variable for SIC being between 2833 and 2836
Computer hardware industry	An indicator variable for SIC being between 3570 and 3577
Computer software industry	An indicator variable for SIC being between 7371 and 7379
Electronics industry	An indicator variable for SIC being between 3600 and 3674
Retailing industry	An indicator variable for SIC being between 5200 and 5961
Panel H: Outcome group: Business failure	
Variable	Definition
Business failure within 3 years	An indicator variable for a business failure within the next 3 years as defined in Ogneva et al. (2020)
Profit ratio	Moving average of quarterly profitability over the prior fiscal year with higher weights assigned to more recent values as in Campbell et al. (2008), where profitability is equal to net income (NIQ) divided by market-valued total assets. Market-valued total assets are a sum of the market value of equity (CSHOQ x PRCCQ) and total liabilties (LTQ)
Total liabilities to total assets	Total liabilities (LT) divided by market-valued total assets at the fiscal year end (defined as previously)
Excess stock return	Moving average of log excess stock return relative to S&P 500 index over prior 12 months, with higher weights assigned to more recent returns as in Campbell et al. (2008)
Sigma	Standard deviation of daily stock returns over the previous three months
Relative size	A logarithm of the ratio of stock's market value of equity to the total market capitalization of the S&P 500 index at the fiscal year-end
Cash to total assets	Cash holdings divided by market-valued total assets at the fiscal year end (defined as previously)
Market-to-book	Market-to-book as computed in Ogneva et al. (2020)
Price	Logarithm of the stock price (PRCC). We set prices above $15 to $15 as in Campbell et al. (2008)
Panel I: Outcome group: Return on assets	
Variable	Definition
Return on assets, adj.	Industry-adjusted ROA, or the difference between ROA for a firm and the median ROA for its industry in that fiscal year (using two-digit Standard Industrial Classification (SIC) codes for industry classification)
Log market value	Log of market value of common equity
Panel J: Outcome group: Firm value	
Variable	Definition
Tobin's Q	Defined as the ratio (TA+MVE BVE)/TA, where TA is total assets (AT), MVE is market capitalization (PRCC_F x CSHO), and BVE is the book value of equity (CEQ)

Table A.1: —*Continued*

Panel K: Outcome group: Stock returns

Variable	Definition
Stock returns, 12-months	Stock returns over 12 months, starting 3 months after the fiscal year end
Log market value	Log of market value of common equity
Book-to-market	Book value of common equity (CEQ) divided by the market value of common equity
Operating profitability	Operating profitability is (REV - COGS - SG&A - XINT)/CEQ
Investment	Investment is the rate of growth of total assets, i.e. ln(AT t-1/AT t-2)

Panel L: Outcome group: Credit ratings

Variable	Definition
S&P credit rating	The S&P credit rating converted into numerical value following Ashbaugh-Skaife et al. (2006)
Investment grade debt	An indicator variable for having an investment-grade debt, i.e., credit rating at or above speculative grade BBB
Log market value	Log of market value of common equity
Book-to-market	Book value of common equity (CEQ) divided by the market value of common equity
Return on assets	Income from operations (OIADP) divided by average total assets (AT)
Leverage	Ratio of book value of debt (DLTT+DLC) to market value of common equity (PRCCF x CSHO)
Beta	Slope from regressing daily returns on CRSP value-weighted index
Volatility, 12-month	Standard deviation of daily returns over 12 months

Figure 1: **Regression tree**

This figure provides a hypothetical example of a regression tree with 2-way interactions between *CEO equity ownership* and *Board tenure* for *Return on assets* outcome. The final predictions are denoted by R_1, R_2, and R_3. The right figure shows the actual tree. The left figure shows the split of the space of characteristics that corresponds to that tree.

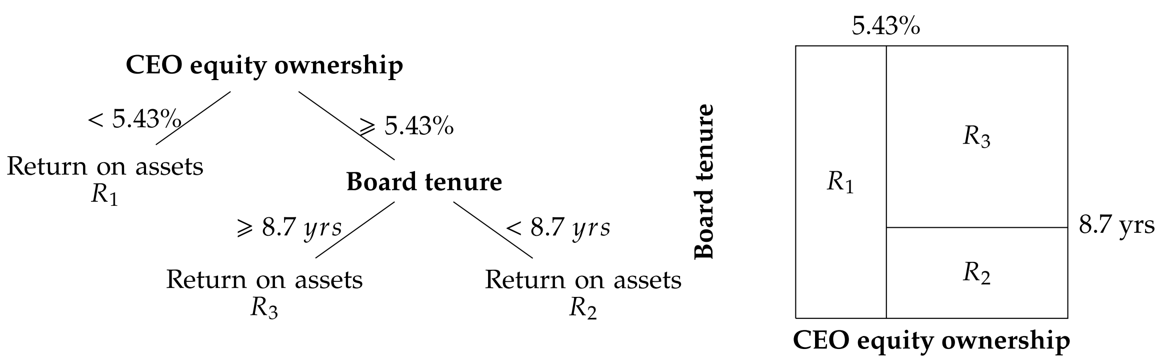
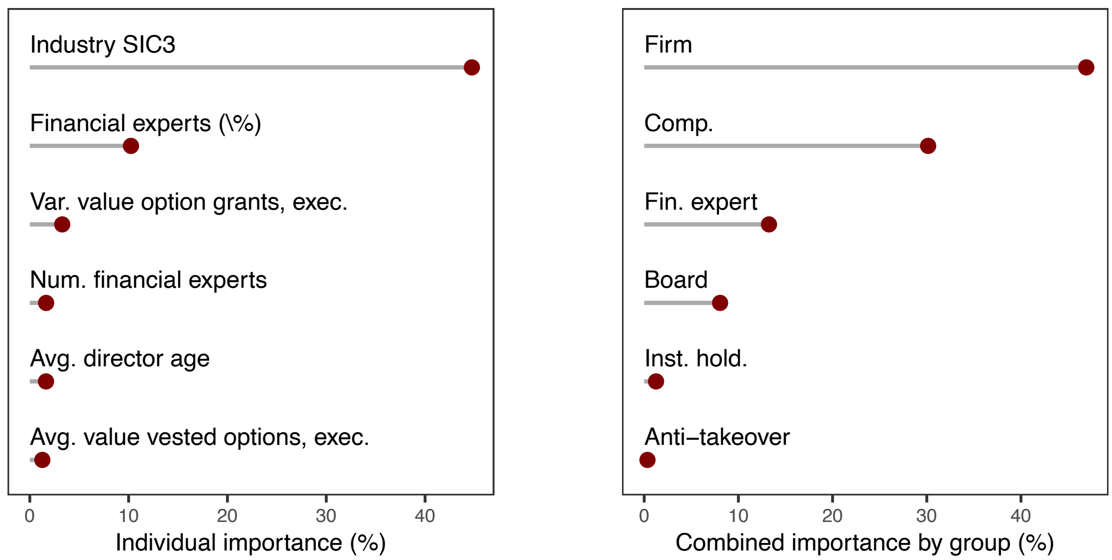


Figure 2: **Variable importance for restatements as in Hennes et al. (2008)**

This figure depicts the relative importance of the top characteristics for predicting restatements as in Hennes et al. (2008) at $t+1$ and $t+3$ from the model that includes both firm and corporate governance characteristics. For each characteristic (left panels), importance is computed as the reduction of the error attributable to this characteristic as described in Friedman (2001) using the estimation sample. For each group of characteristics (right panels), importance is computed as the sum of individual importance values of characteristics in that group. *Firm* denotes firm characteristics. *Inst. hold.* denotes institutional investor holdings. *Anti-takeover* denotes anti-takeover provisions. *Comp.* denotes executive compensation. *Fin. expert* denotes board's financial expertise. *Board* denotes board characteristics.

(a) **Restatements as in Hennes et al. (2008)** $t+1$



(b) **Restatements as in Hennes et al. (2008)** $t+3$

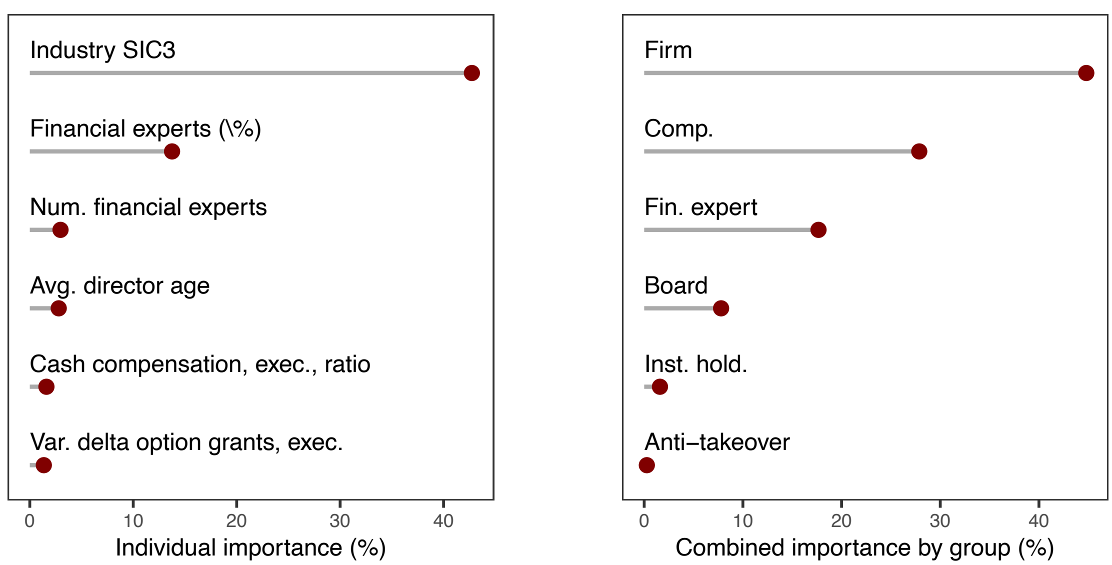
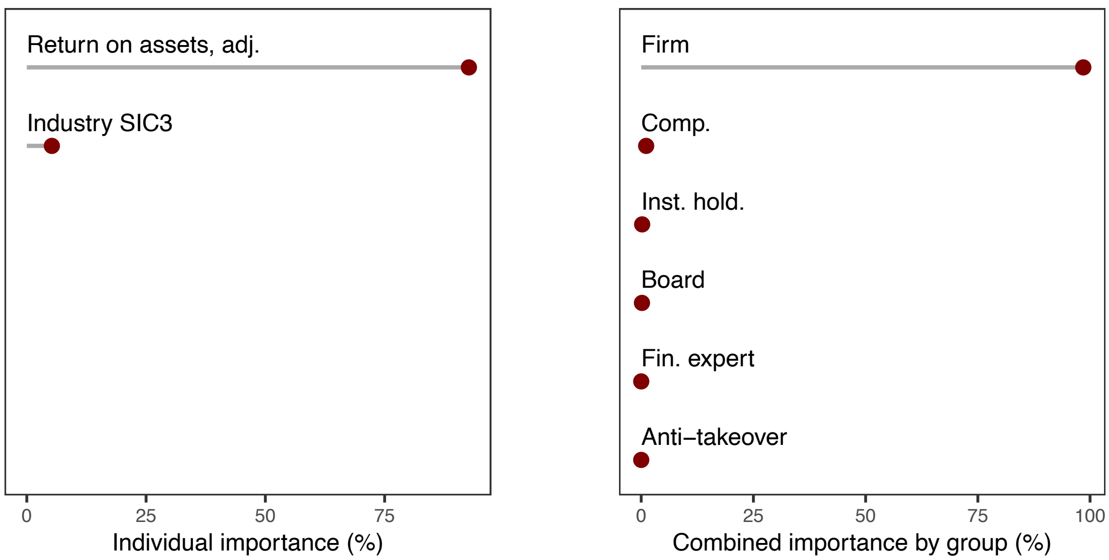


Figure 3: **Variable importance for operating performance**

This figure depicts the relative importance of the top characteristics for predicting operating performance at $t + 1$ and $t + 3$ from the model that includes both firm and corporate governance characteristics. For each characteristic (left panels), importance is computed as the reduction of the error attributable to this characteristic as described in Friedman (2001) using the estimation sample. For each group of characteristics (right panels), importance is computed as the sum of individual importance values of characteristics in that group. *Firm* denotes firm characteristics. *Inst. hold.* denotes institutional investor holdings. *Anti-takeover* denotes anti-takeover provisions. *Comp.* denotes executive compensation. *Fin. expert* denotes board's financial expertise. *Board* denotes board characteristics.

(a) **Return on assets, adj.** $t + 1$



(b) **Return on assets, adj.** $t + 3$

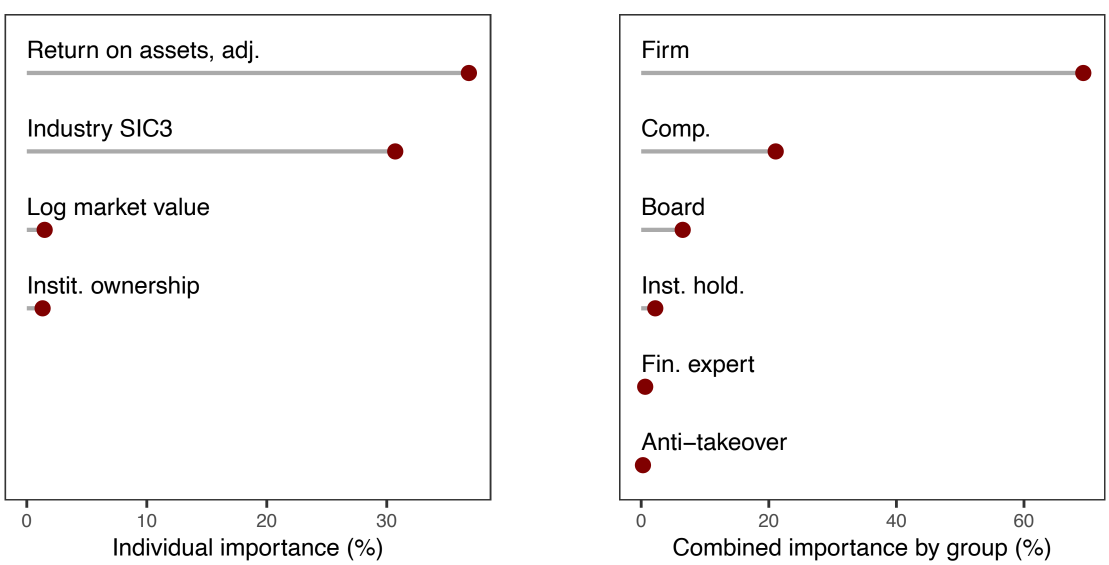
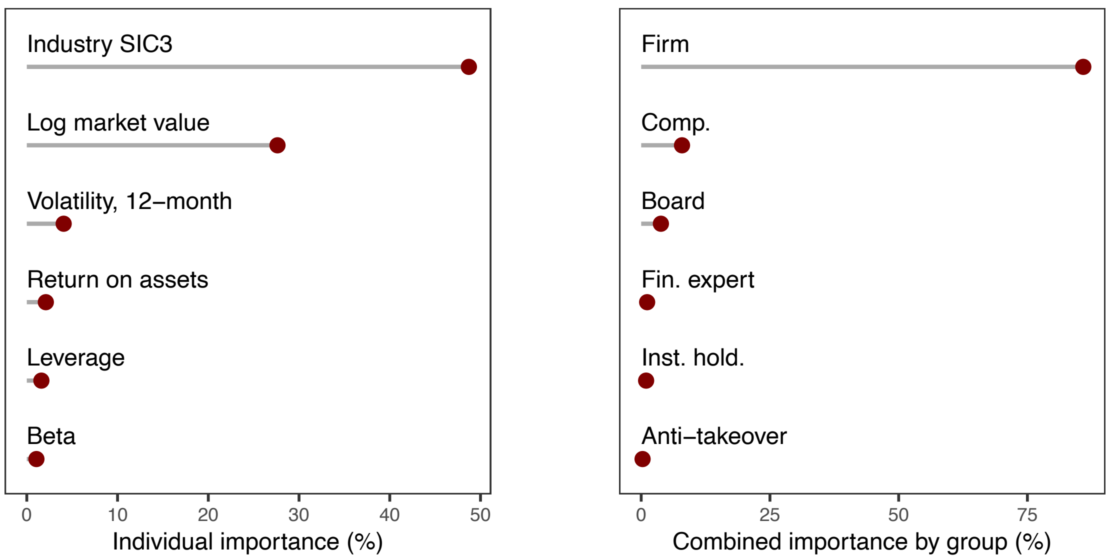


Figure 4: **Variable importance for S&P credit rating**

This figure depicts the relative importance of the top characteristics for predicting S&P credit rating at $t+1$ and $t+3$ from the model that includes both firm and corporate governance characteristics. For each characteristic (left panels), importance is computed as the reduction of the error attributable to this characteristic as described in Friedman (2001) using the estimation sample. For each group of characteristics (right panels), importance is computed as the sum of individual importance values of characteristics in that group. *Firm* denotes firm characteristics. *Inst. hold.* denotes institutional investor holdings. *Anti-takeover* denotes anti-takeover provisions. *Comp.* denotes executive compensation. *Fin. expert* denotes board's financial expertise. *Board* denotes board characteristics.

(a) **S&P credit rating** $t+1$



(b) **S&P credit rating** $t+3$

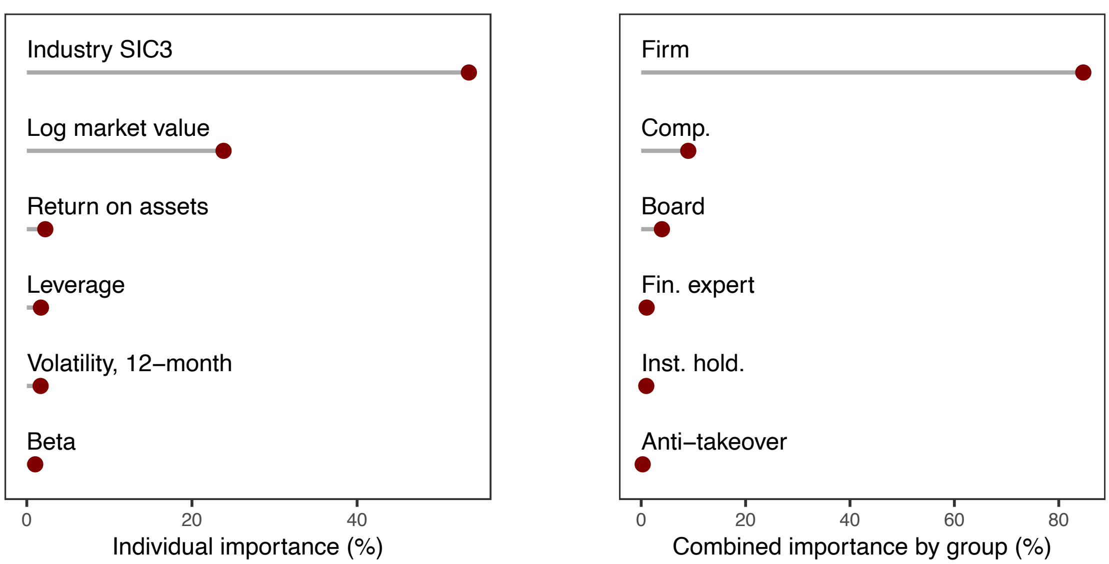


Table 1: **Summary statistics**

This table provides descriptive statistics for the variables used in the analyses defined in Table A.1. All variables are winsorized at the 1st and 99th percentiles.

Panel A: Corporate governance: Institutional investor holdings

Variable	Obs.	Mean	SD	Q25	Median	Q75
Instit. ownership	50,439	60.689	27.347	39.530	65.211	83.352
Instit. ownership., top 5	50,439	27.107	12.639	18.990	26.201	33.915
Blockholder	50,439	18.562	15.428	6.461	15.796	27.407

Panel B: Corporate governance: Anti-takeover provisions

Variable	Obs.	Mean	SD	Q25	Median	Q75
PA, OH, WI, MA incorporated	50,439	0.073	0.261	0.000	0.000	0.000
Staggered board	50,439	0.462	0.499	0.000	0.000	1.000
Unequal voting rights	50,439	0.089	0.285	0.000	0.000	0.000
Poison pill	50,439	0.267	0.442	0.000	0.000	1.000
Supermajority to amend charter	50,439	0.211	0.408	0.000	0.000	0.000
Supermajority to approve mergers	50,439	0.409	0.492	0.000	0.000	1.000
Supermajority to amend bylaws	50,439	0.550	0.498	0.000	1.000	1.000

Panel C: Corporate governance: Executive compensation

Variable	Obs.	Mean	SD	Q25	Median	Q75
Shares held (%), CEO	50,439	4.193	9.618	0.174	0.651	2.716
Total shares held (%), exec.	50,439	2.440	6.697	0.161	0.484	1.417
Avg. shares held (%), exec.	50,439	0.640	1.735	0.040	0.122	0.379
Var. shares held (%), exec.	50,439	8.799	48.510	0.001	0.007	0.100
Stock awards, CEO	50,439	1.029	1.966	0.000	0.089	1.146
Avg. stock awards, exec.	50,439	0.330	0.613	0.000	0.069	0.380
Var. stock awards, exec.	50,439	0.197	0.817	0.000	0.001	0.033
Stock awards, exec., ratio	50,439	0.233	0.389	0.000	0.017	0.426
Cash compensation, CEO	50,439	1.511	1.596	0.545	0.962	1.853
Avg. cash compensation, exec.	50,439	0.689	0.605	0.319	0.489	0.822
Avg. cash compensation, exec.	50,439	0.240	0.938	0.004	0.016	0.075
Cash compensation, exec., ratio	50,439	0.312	0.278	0.132	0.267	0.466
Value option grants, CEO	50,439	0.964	2.110	0.000	0.035	0.920
Avg. value option grants, exec.	50,439	0.295	0.592	0.000	0.054	0.308
Var. value option grants, exec.	50,439	0.253	1.110	0.000	0.001	0.033
Value option grants, exec., ratio	50,439	0.214	0.400	0.000	0.000	0.374
Value vested options, CEO	50,439	5.722	13.009	0.027	0.959	4.799
Avg. value vested options, exec.	50,439	1.132	2.295	0.044	0.293	1.082
Var. value vested options, exec.	50,439	6.722	30.715	0.001	0.064	0.905
Value vested options, exec., ratio	50,439	0.558	0.762	0.000	0.335	1.030
Value non-vested options, CEO	50,439	1.684	3.816	0.000	0.187	1.469
Avg. value non-vested options, exec.	50,439	0.474	1.000	0.000	0.096	0.453
Var. value non-vested options, exec.	50,439	0.682	3.072	0.000	0.004	0.088
Value non-vested options, exec., ratio	50,439	0.289	0.489	0.000	0.070	0.521
Value shares held, CEO	50,439	40.777	128.583	1.269	5.430	19.999
Avg. value shares held, exec.	50,439	5.634	18.388	0.232	0.927	2.953
Var. value shares held, exec.	50,439	1,185.883	7,857.835	0.035	0.543	6.749
Value shares held, exec., ratio	50,439	1.133	1.365	0.302	0.958	1.711
Delta option grants, CEO	50,439	0.016	0.035	0.000	0.001	0.015
Avg. delta option grants, exec.	50,439	0.005	0.010	0.000	0.001	0.005
Var. delta option grants, exec.	50,439	0.000	0.000	0.000	0.000	0.000
Delta option grants, exec., ratio	50,439	0.011	0.025	0.000	0.000	0.010

Table 1: —*Continued*

Variable	Obs.	Mean	SD	Q25	Median	Q75
Delta vested options, CEO	50,439	0.093	0.206	0.001	0.017	0.079
Avg. delta vested options, exec.	50,439	0.019	0.038	0.001	0.005	0.018
Var. delta vested options, exec.	50,439	0.002	0.007	0.000	0.000	0.000
Delta vested options, exec., ratio	50,439	0.058	0.122	0.000	0.010	0.057
Delta non-vested options, CEO	50,439	0.027	0.062	0.000	0.003	0.024
Avg. delta non-vested options, exec.	50,439	0.008	0.016	0.000	0.002	0.007
Var. delta non-vested options, exec.	50,439	0.000	0.001	0.000	0.000	0.000
Delta non-vested options, exec., ratio	50,439	0.018	0.043	0.000	0.001	0.016
Delta shares held, CEO	50,439	1.895	5.468	0.085	0.293	1.027
Avg. delta shares held, exec.	50,439	0.260	0.782	0.016	0.051	0.144
Var. delta shares held, exec.	50,439	2.103	12.957	0.000	0.002	0.017
Delta shares held, exec., ratio	50,439	0.408	0.703	0.035	0.171	0.530
Vega option grants, CEO	50,439	0.015	0.032	0.000	0.000	0.013
Avg. vega option grants, exec.	50,439	0.004	0.009	0.000	0.001	0.004
Var. vega option grants, exec.	50,439	0.000	0.000	0.000	0.000	0.000
Vega option grants, exec., ratio	50,439	0.010	0.023	0.000	0.000	0.008
Vega vested options, CEO	50,439	0.034	0.073	0.000	0.007	0.030
Avg. vega vested options, exec.	50,439	0.008	0.016	0.000	0.002	0.008
Var. vega vested options, exec.	50,439	0.000	0.001	0.000	0.000	0.000
Vega vested options, exec., ratio	50,439	0.024	0.052	0.000	0.004	0.022
Vega non-vested options, CEO	50,439	0.018	0.040	0.000	0.002	0.015
Avg. vega non-vested options, exec.	50,439	0.005	0.010	0.000	0.001	0.005
Var. vega non-vested options, exec.	50,439	0.000	0.000	0.000	0.000	0.000
Vega non-vested options, exec., ratio	50,439	0.012	0.029	0.000	0.001	0.010
Value all equity, CEO	50,439	50.306	135.823	3.425	10.825	33.457
Avg. value all equity, exec.	50,439	7.739	20.233	0.740	2.081	5.611
Var. value all equity, exec.	50,439	1,295.718	8,365.271	0.189	1.927	18.415
Value all equity, exec., ratio	50,439	1.255	1.141	0.593	1.153	1.760
Delta all equity, CEO	50,439	2.050	5.528	0.147	0.433	1.276
Avg. delta all equity, exec.	50,439	0.294	0.798	0.030	0.076	0.192
Var. delta all equity, exec.	50,439	2.137	13.058	0.000	0.003	0.026
Delta all equity, exec., ratio	50,439	0.455	0.691	0.068	0.238	0.608
Vega all equity, CEO	50,439	0.068	0.130	0.002	0.019	0.067
Avg. vega all equity, exec.	50,439	0.017	0.031	0.001	0.006	0.018
Var. vega all equity, exec.	50,439	0.001	0.002	0.000	0.000	0.000
Vega all equity, exec., ratio	50,439	0.043	0.080	0.001	0.011	0.046
Value vested equity, CEO	50,439	47.243	133.725	2.542	8.841	28.917
Avg. value vested equity, exec.	50,439	6.884	19.537	0.521	1.590	4.493
Var. value vested equity, exec.	50,439	1,266.779	8,240.708	0.133	1.443	14.496
Value vested equity, exec., ratio	50,439	1.237	1.238	0.509	1.123	1.804
Delta vested equity, CEO	50,439	2.001	5.518	0.124	0.386	1.196
Avg. delta vested equity, exec.	50,439	0.281	0.792	0.024	0.066	0.173
Var. delta vested equity, exec.	50,439	2.130	13.045	0.000	0.002	0.023
Delta vested equity, exec., ratio	50,439	0.442	0.697	0.057	0.218	0.589
Vega vested equity, CEO	50,439	0.034	0.073	0.000	0.007	0.030
Avg. vega vested equity, exec.	50,439	0.008	0.016	0.000	0.002	0.008
Var. vega vested equity, exec.	50,439	0.000	0.001	0.000	0.000	0.000
Vega vested equity, exec., ratio	50,439	0.024	0.052	0.000	0.004	0.022
Value all equity log-growth, CEO	50,439	0.000	0.000	−0.000	0.000	0.000
Avg. value all equity log-growth, exec.	50,439	0.000	0.000	−0.000	0.000	0.000

Table 1: —*Continued*

Variable	Obs.	Mean	SD	Q25	Median	Q75
Var. value all equity log-growth, exec.	50,439	0.000	0.000	0.000	0.000	0.000
Value all equity log-growth, exec., ratio	50,439	−0.000	0.000	−0.000	−0.000	0.000
Delta all equity log-growth, CEO	50,439	0.000	0.000	−0.000	0.000	0.000
Avg. delta all equity log-growth, exec.	50,439	0.000	0.000	−0.000	0.000	0.000
Var. delta all equity log-growth, exec.	50,439	0.000	0.000	0.000	0.000	0.000
Delta all equity log-growth, exec., ratio	50,439	−0.000	0.000	−0.000	−0.000	0.000
Vega all equity log-growth, CEO	50,439	0.000	0.000	−0.000	0.000	0.000
Avg. vega all equity log-growth, exec.	50,439	0.000	0.000	−0.000	0.000	0.000
Var. vega all equity log-growth, exec.	50,439	0.000	0.000	0.000	0.000	0.000
Vega all equity log-growth, exec., ratio	50,439	−0.000	0.000	−0.000	0.000	0.000

Panel D: Corporate governance: Board's financial expertise

Variable	Obs.	Mean	SD	Q25	Median	Q75
Num. financial experts	50,439	1.498	1.106	1.000	1.000	2.000
Financial experts (%)	50,439	18.258	13.146	11.111	14.286	25.000
Num. audit insiders	50,439	0.000	0.000	0.000	0.000	0.000
Audit insiders (%)	50,439	0.000	0.000	0.000	0.000	0.000
Num. finance insiders	50,439	0.067	0.298	0.000	0.000	0.000
Finance insiders (%)	50,439	1.493	6.702	0.000	0.000	0.000
Num. audit directors	50,439	3.609	0.936	3.000	3.000	4.000
Audit directors (%)	50,439	44.179	11.978	36.364	42.857	50.000
Num. finance directors	50,439	0.605	1.564	0.000	0.000	0.000
Finance directors (%)	50,439	6.100	15.567	0.000	0.000	0.000

Panel E: Corporate governance: Board characteristics

Variable	Obs.	Mean	SD	Q25	Median	Q75
Num. post-CEO directors	50,439	4.049	2.699	2.000	4.000	6.000
Post-CEO directors (%)	50,439	48.176	29.686	22.222	50.000	77.778
Num. over 69 directors	50,439	1.054	1.235	0.000	1.000	2.000
Over 69 directors (%)	50,439	12.433	14.385	0.000	10.000	20.000
Avg. director age	50,439	59.039	4.644	56.167	59.333	62.143
Num. busy directors	50,439	1.298	1.492	0.000	1.000	2.000
Busy directors (%)	50,439	14.625	15.845	0.000	12.500	25.000
Num. directors	50,439	8.515	2.342	7.000	8.000	10.000
CEO Chairman of the board	50,439	0.483	0.500	0.000	0.000	1.000
Num. CEO directors	50,439	0.300	0.617	0.000	0.000	0.000
CEO directors (%)	50,439	3.304	6.668	0.000	0.000	0.000
Num. outsider directors	50,439	6.211	2.307	4.000	6.000	8.000
Outsider directors (%)	50,439	72.426	15.438	62.500	75.000	85.714
Num. insider directors	50,439	1.527	0.855	1.000	1.000	2.000
Insider directors (%)	50,439	18.693	10.120	11.111	14.286	25.000
Num. affiliate directors	50,439	0.766	1.122	0.000	0.000	1.000
Affiliate directors (%)	50,439	8.782	12.542	0.000	0.000	14.286
Board tenure	50,439	9.156	4.348	5.967	8.700	11.831
Female directors (%)	50,439	9.792	10.097	0.000	10.000	16.670
Total equity, director	50,439	10.407	23.424	0.312	1.510	9.080
Avg. equity, director	50,439	1.488	3.333	0.043	0.218	1.263
Var. total equity, director	50,439	36.601	137.272	0.002	0.088	5.466
Num. nomination insiders	50,439	0.014	0.119	0.000	0.000	0.000

Table 1: —*Continued*

Variable	Obs.	Mean	SD	Q25	Median	Q75
Nomination insiders (%)	50,439	1.447	11.943	0.000	0.000	0.000
Num. compensation insiders	50,439	0.028	0.165	0.000	0.000	0.000
Compensation insiders (%)	50,439	0.814	4.886	0.000	0.000	0.000
Num. compliance insiders	50,439	0.000	0.000	0.000	0.000	0.000
Compliance insiders (%)	50,439	0.000	0.000	0.000	0.000	0.000
Num. governance insiders	50,439	0.023	0.149	0.000	0.000	0.000
Governance insiders (%)	50,439	0.634	4.285	0.000	0.000	0.000
Num. nomination directors	50,439	0.014	0.119	0.000	0.000	0.000
Nomination directors (%)	50,439	0.167	1.397	0.000	0.000	0.000
Num. compensation directors	50,439	3.512	1.067	3.000	3.000	4.000
Compensation directors (%)	50,439	42.864	13.425	33.333	42.857	50.000
Num. compliance directors	50,439	0.130	0.661	0.000	0.000	0.000
Compliance directors (%)	50,439	1.406	7.113	0.000	0.000	0.000
Num. governance directors	50,439	2.855	1.839	2.000	3.000	4.000
Governance directors (%)	50,439	34.281	22.231	23.077	37.500	50.000
Avg. value shares held, director	50,439	14.629	47.516	0.410	1.373	6.111
Var. value shares held, director	50,439	9,371.180	54,117.210	0.153	3.309	126.970
Value shares held, director, ratio	50,439	0.759	1.713	−0.113	0.780	1.804

Panel F: Outcome group: Restatements of financial statements

Variable	Obs.	Mean	SD	Q25	Median	Q75
Restatements as in Hennes et al. (2008) $_{t+1}$	44,391	0.018	0.134	0.000	0.000	0.000
Restatements as in Hennes et al. (2008) $_{t+3}$	40,014	0.012	0.108	0.000	0.000	0.000
RSST accruals	44,391	0.033	0.196	−0.029	0.016	0.079
Receivables growth	44,391	0.015	0.054	−0.006	0.006	0.029
Inventory growth	44,391	0.005	0.031	−0.001	0.000	0.009
Soft assets	44,391	0.578	0.271	0.365	0.607	0.811
Cash sales growth	44,391	0.055	0.205	−0.024	0.038	0.134
Return on assets, growth	44,391	0.001	0.134	−0.025	0.000	0.023
Issuance	44,391	0.925	0.264	1.000	1.000	1.000

Panel G: Outcome group: Return on assets

Variable	Obs.	Mean	SD	Q25	Median	Q75
Return on assets, adj. $_{t+1}$	47,866	0.018	0.170	−0.020	0.011	0.076
Return on assets, adj. $_{t+3}$	43,113	0.021	0.169	−0.018	0.011	0.074
Log market value	47,866	6.607	1.751	5.389	6.526	7.765
Return on assets, adj.	47,866	0.019	0.169	−0.019	0.012	0.079

Panel H: Outcome group: Credit ratings

Variable	Obs.	Mean	SD	Q25	Median	Q75
S&P credit rating $_{t+1}$	16,962	3.466	1.086	3.000	3.917	4.000
S&P credit rating $_{t+3}$	13,339	3.515	1.083	3.000	4.000	4.000
Log market value	16,962	7.955	1.507	6.951	7.920	9.002
Book-to-market	16,962	0.554	0.426	0.276	0.473	0.720
Return on assets	16,962	0.080	0.073	0.038	0.072	0.116
Leverage	16,962	0.337	0.205	0.190	0.314	0.455
Beta	16,962	1.126	0.489	0.786	1.059	1.402
Volatility, 12-month	16,962	0.391	0.224	0.238	0.327	0.468

Table 2: **Optimal GBM parameters and cross-validation errors**

This table presents optimal meta-parameters for the gradient boosting of regression trees models (GBM) selected on the training data by the cross-validation procedure in Section 4. We chose the tree depth, i.e., the level of interaction between variables, and the number of trees, i.e., the number of terms in the model, to minimize cross-validation errors.

Panel A: Restatements as in Hennes et al. (2008)

	$t+1$				$t+3$			
Model	Obs.	Tree depth	Trees	Error	Obs.	Tree depth	Trees	Error
Models with firm characteristics								
Firm	31,872	5	160	0.221	23,712	7	135	0.187
Firm, Inst. hold.	31,872	7	170	0.217	23,712	7	150	0.186
Firm, Anti-takeover	31,872	7	155	0.219	23,712	7	140	0.187
Firm, Comp.	31,872	5	235	0.215	23,712	7	165	0.185
Firm, Fin. expert	31,872	7	175	0.216	23,712	7	165	0.179
Firm, Board	31,872	7	195	0.216	23,712	7	165	0.183
Firm, All govern.	31,872	7	215	0.213	23,712	7	170	0.181
Models without firm characteristics								
Inst. hold.	31,872	7	365	0.244	23,712	7	240	0.211
Anti-takeover	31,872	7	190	0.247	23,712	7	210	0.212
Comp.	31,872	2	900	0.229	23,712	2	660	0.200
Fin. expert	31,872	3	405	0.240	23,712	3	490	0.197
Board	31,872	3	1,490	0.228	23,712	5	800	0.196
All govern.	31,872	2	1,120	0.221	23,712	2	870	0.192

Table 2: —*Continued*

Panel B: Return on assets, adj.

Model	$t+1$				$t+3$			
	Obs.	Tree depth	Trees	Error	Obs.	Tree depth	Trees	Error
	Models with firm characteristics							
Firm	37,345	3	1,050	0.086	33,645	5	780	0.114
Firm, Inst. hold.	37,345	3	1,650	0.086	33,645	5	1,050	0.113
Firm, Anti-takeover	37,345	3	1,490	0.086	33,645	5	790	0.114
Firm, Comp.	37,345	3	1,050	0.086	33,645	7	2,650	0.111
Firm, Fin. expert	37,345	3	770	0.086	33,645	7	495	0.114
Firm, Board	37,345	5	425	0.086	33,645	7	5,800	0.112
Firm, All govern.	37,345	3	1,380	0.086	33,645	7	15,750	0.109
	Models without firm characteristics							
Inst. hold.	37,345	1	2,350	0.159	33,645	1	1,480	0.161
Anti-takeover	37,345	5	660	0.167	33,645	5	1,160	0.167
Comp.	37,345	7	9,700	0.148	33,645	7	8,550	0.151
Fin. expert	37,345	2	640	0.166	33,645	2	570	0.166
Board	37,345	7	23,500	0.149	33,645	7	22,800	0.152
All govern.	37,345	7	42,700	0.138	33,645	7	44,000	0.142

Table 2: —*Continued*

Panel C: S&P credit rating

Model	$t+1$				$t+3$			
	Obs.	Tree depth	Trees	Error	Obs.	Tree depth	Trees	Error
				Models with firm characteristics				
Firm	12,969	7	5,100	0.562	9,672	7	3,600	0.607
Firm, Inst. hold.	12,969	7	6,800	0.549	9,672	7	4,950	0.595
Firm, Anti-takeover	12,969	7	7,650	0.541	9,672	7	6,100	0.588
Firm, Comp.	12,969	7	10,200	0.526	9,672	7	9,350	0.579
Firm, Fin. expert	12,969	7	6,550	0.542	9,672	7	6,000	0.592
Firm, Board	12,969	7	20,850	0.496	9,672	7	20,900	0.538
Firm, All govern.	12,969	7	20,650	0.486	9,672	7	19,900	0.540
				Models without firm characteristics				
Inst. hold.	12,969	5	590	0.969	9,672	3	820	0.973
Anti-takeover	12,969	5	3,550	1.057	9,672	5	7,500	1.060
Comp.	12,969	7	12,000	0.723	9,672	7	4,000	0.798
Fin. expert	12,969	2	1,170	0.959	9,672	2	1,200	0.978
Board	12,969	7	37,850	0.686	9,672	7	30,950	0.734
All govern.	12,969	7	40,850	0.618	9,672	7	32,550	0.694

Table 3: **Mean out-of-sample errors and t-statistics for restatements as in Hennes et al. (2008): Firm characteristics vs firm and governance characteristics**

This table reports mean out-of-sample test errors in the first column and t-statistics for the differences in these errors. With t-statistics, we compare the model in the column to the model in the corresponding row. *Base model* denotes an uninformed baseline that uses an average outcome in the estimation data for prediction. *Firm* denotes firm characteristics. *Inst. hold.* denotes institutional investor holdings. *Anti-takeover* denotes anti-takeover provisions. *Comp.* denotes executive compensation. *Fin. expert* denotes board's financial expertise. *Board* denotes board characteristics. *All govern.* denotes all governance characteristics that is the union of *Inst. hold.*, *Anti-takeover*, *Comp.*, *Fin. expert*, and *Board*.

Panel A: Restatements as in Hennes et al. (2008) $t+1$

2013	Error	Firm	Firm, Inst. hold.	Firm, Anti-takeover	Firm, Comp.	Firm, Fin. expert	Firm, Board	Firm, All govern.
Base model	0.186	2.151**	2.245**	2.277**	2.456**	2.493**	2.418**	2.507**
Firm	0.158		0.118	0.123	0.393	0.419	0.308	0.466
Firm, Inst. hold.	0.156			0.004	0.276	0.301	0.190	0.350
Firm, Anti-takeover	0.156				0.276	0.301	0.188	0.350
Firm, Comp.	0.152					0.023	−0.090	0.074
Firm, Fin. expert	0.152						−0.114	0.053
Firm, Board	0.153							0.165
Firm, All govern.	0.151							
2014	**Error**	**Firm**	**Firm, Inst. hold.**	**Firm, Anti-takeover**	**Firm, Comp.**	**Firm, Fin. expert**	**Firm, Board**	**Firm, All govern.**
Base model	0.170	2.630***	2.832***	2.770***	3.226***	3.017***	2.974***	3.197***
Firm	0.141		0.211	0.143	0.701	0.513	0.419	0.718
Firm, Inst. hold.	0.139			−0.068	0.496	0.311	0.212	0.516
Firm, Anti-takeover	0.139				0.563	0.377	0.279	0.582
Firm, Comp.	0.133					−0.175	−0.279	0.029
Firm, Fin. expert	0.135						−0.100	0.200
Firm, Board	0.136							0.303
Firm, All govern.	0.133							
2015	**Error**	**Firm**	**Firm, Inst. hold.**	**Firm, Anti-takeover**	**Firm, Comp.**	**Firm, Fin. expert**	**Firm, Board**	**Firm, All govern.**
Base model	0.152	3.224***	3.462***	3.418***	4.189***	3.879***	3.833***	4.238***
Firm	0.124		0.272	0.242	1.091	0.822	0.722	1.201
Firm, Inst. hold.	0.122			−0.028	0.819	0.557	0.453	0.934
Firm, Anti-takeover	0.122				0.843	0.581	0.478	0.956
Firm, Comp.	0.115					−0.244	−0.360	0.128
Firm, Fin. expert	0.117						−0.110	0.365
Firm, Board	0.118							0.481
Firm, All govern.	0.114							

Table 3: —*Continued*

Panel B: Restatements as in Hennes et al. (2008) $t + 3$

2011	Error	Firm	Firm, Inst. hold.	Firm, Anti-takeover	Firm, Comp.	Firm, Fin. expert	Firm, Board	Firm, All govern.
Base model	0.178	2.060**	2.069**	2.046**	2.074**	2.236**	2.221**	2.130**
Firm	0.145		0.028	−0.008	0.068	0.338	0.219	0.236
Firm, Inst. hold.	0.144			−0.036	0.040	0.310	0.190	0.208
Firm, Anti-takeover	0.145				0.076	0.345	0.226	0.243
Firm, Comp.	0.144					0.268	0.147	0.168
Firm, Fin. expert	0.139						−0.128	−0.095
Firm, Board	0.141							0.029
Firm, All govern.	0.141							
2012	**Error**	**Firm**	**Firm, Inst. hold.**	**Firm, Anti-takeover**	**Firm, Comp.**	**Firm, Fin. expert**	**Firm, Board**	**Firm, All govern.**
Base model	0.162	2.302**	2.333**	2.304**	2.382**	2.683***	2.443**	2.514**
Firm	0.129		0.058	0.015	0.134	0.552	0.227	0.387
Firm, Inst. hold.	0.129			−0.043	0.076	0.492	0.169	0.329
Firm, Anti-takeover	0.129				0.119	0.536	0.212	0.372
Firm, Comp.	0.127					0.416	0.093	0.255
Firm, Fin. expert	0.121						−0.322	−0.152
Firm, Board	0.126							0.164
Firm, All govern.	0.124							
2013	**Error**	**Firm**	**Firm, Inst. hold.**	**Firm, Anti-takeover**	**Firm, Comp.**	**Firm, Fin. expert**	**Firm, Board**	**Firm, All govern.**
Base model	0.139	2.118**	2.165**	2.107**	2.243**	2.655***	2.370**	2.581***
Firm	0.114		0.087	0.010	0.165	0.626	0.308	0.566
Firm, Inst. hold.	0.112			−0.076	0.077	0.533	0.218	0.474
Firm, Anti-takeover	0.113				0.154	0.612	0.295	0.552
Firm, Comp.	0.111					0.458	0.141	0.399
Firm, Fin. expert	0.105						−0.317	−0.055
Firm, Board	0.109							0.259
Firm, All govern.	0.106							

Table 4: **Mean out-of-sample errors and t-statistics for restatements as in Hennes et al. (2008): Firm characteristics vs governance characteristics**

This table reports mean out-of-sample test errors in the first column and t-statistics for the differences in these errors. With t-statistics, we compare the model in the column to the model in the corresponding row. *Base model* denotes an uninformed baseline that uses an average outcome in the estimation data for prediction. *Firm* denotes firm characteristics. *Inst. hold.* denotes institutional investor holdings. *Anti-takeover* denotes anti-takeover provisions. *Comp.* denotes executive compensation. *Fin. expert* denotes board's financial expertise. *Board* denotes board characteristics. *All govern.* denotes all governance characteristics that is the union of *Inst. hold.*, *Anti-takeover*, *Comp.*, *Fin. expert*, and *Board*.

Panel A: Restatements as in Hennes et al. (2008) $t + 1$

2013	Error	Firm	Inst. hold.	Anti-takeover	Comp.	Fin. expert	Board	All govern.
Base model	0.186	2.151**	0.249	0.316	1.152	0.782	1.003	1.153
Firm	0.158		−1.810*	−1.726*	−0.640	−1.162	−0.716	−0.499
Inst. hold.	0.183			0.066	0.908	0.527	0.773	0.929
Anti-takeover	0.182				0.844	0.461	0.713	0.871
Comp.	0.168					−0.402	−0.091	0.081
Fin. expert	0.175						0.292	0.461
Board	0.170							0.165
All govern.	0.166							
2014	**Error**	**Firm**	**Inst. hold.**	**Anti-takeover**	**Comp.**	**Fin. expert**	**Board**	**All govern.**
Base model	0.170	2.630***	0.400	0.573	1.928*	1.196	1.481	1.933*
Firm	0.141		−2.154**	−1.931*	−0.235	−1.179	−0.537	−0.023
Inst. hold.	0.165			0.176	1.556	0.804	1.142	1.598
Anti-takeover	0.163				1.383	0.626	0.987	1.442
Comp.	0.144					−0.779	−0.280	0.168
Fin. expert	0.155						0.434	0.890
Board	0.149							0.421
All govern.	0.141							
2015	**Error**	**Firm**	**Inst. hold.**	**Anti-takeover**	**Comp.**	**Fin. expert**	**Board**	**All govern.**
Base model	0.152	3.224***	0.872	0.706	2.856***	1.917*	3.066***	3.336***
Firm	0.124		−2.385**	−2.169**	0.309	−0.989	0.501	0.919
Inst. hold.	0.144			−0.069	2.181**	1.144	2.388**	2.696***
Anti-takeover	0.145				2.065**	1.095	2.253**	2.555**
Comp.	0.121					−1.093	0.160	0.538
Fin. expert	0.134						1.276	1.630
Board	0.119							0.387
All govern.	0.114							

Table 4: —*Continued*

Panel B: Restatements as in Hennes et al. (2008) $t + 3$

2011	Error	Firm	Inst. hold.	Anti-takeover	Comp.	Fin. expert	Board	All govern.
Base model	0.178	2.060**	−0.045	0.171	0.517	0.492	0.738	0.712
Firm	0.145		−1.918*	−1.810*	−1.206	−1.207	−1.004	−0.884
Inst. hold.	0.179			0.200	0.522	0.500	0.728	0.708
Anti-takeover	0.175				0.357	0.336	0.571	0.560
Comp.	0.168					−0.016	0.189	0.207
Fin. expert	0.168						0.202	0.220
Board	0.164							0.031
All govern.	0.163							
2012	**Error**	**Firm**	**Inst. hold.**	**Anti-takeover**	**Comp.**	**Fin. expert**	**Board**	**All govern.**
Base model	0.162	2.302**	0.167	0.249	0.697	0.774	0.816	0.702
Firm	0.129		−2.031**	−1.981**	−1.152	−1.143	−1.060	−0.965
Inst. hold.	0.160			0.077	0.539	0.607	0.652	0.560
Anti-takeover	0.159				0.478	0.545	0.591	0.504
Comp.	0.150					0.045	0.094	0.063
Fin. expert	0.149						0.051	0.023
Board	0.148							−0.023
All govern.	0.148							
2013	**Error**	**Firm**	**Inst. hold.**	**Anti-takeover**	**Comp.**	**Fin. expert**	**Board**	**All govern.**
Base model	0.139	2.118**	0.486	0.154	1.370	1.271	1.387	1.864*
Firm	0.114		−1.671*	−1.780*	−0.514	−0.589	−0.434	0.026
Inst. hold.	0.134			−0.281	0.964	0.870	0.996	1.475
Anti-takeover	0.137				1.132	1.044	1.159	1.603
Comp.	0.121					−0.074	0.058	0.485
Fin. expert	0.122						0.130	0.553
Board	0.120							0.416
All govern.	0.113							

Table 5: **Mean out-of-sample errors and t-statistics for operating performance: Firm characteristics vs firm and governance characteristics**

This table reports mean out-of-sample test errors in the first column and t-statistics for the differences in these errors. With t-statistics, we compare the model in the column to the model in the corresponding row. *Base model* denotes an uninformed baseline that uses an average outcome in the estimation data for prediction. *Firm* denotes firm characteristics. *Inst. hold.* denotes institutional investor holdings. *Anti-takeover* denotes anti-takeover provisions. *Comp.* denotes executive compensation. *Fin. expert* denotes board's financial expertise. *Board* denotes board characteristics. *All govern.* denotes all governance characteristics that is the union of *Inst. hold.*, *Anti-takeover*, *Comp.*, *Fin. expert*, and *Board*.

Panel A: Return on assets, adj. $t+1$

2014	Error	Firm	Firm, Inst. hold.	Firm, Anti-takeover	Firm, Comp.	Firm, Fin. expert	Firm, Board	Firm, All govern.
Base model	0.181	13.662***	13.754***	13.733***	13.645***	13.606***	13.548***	13.767***
Firm	0.099		0.058	0.058	−0.013	−0.052	−0.118	0.094
Firm, Inst. hold.	0.099			0.000	−0.071	−0.111	−0.176	0.037
Firm, Anti-takeover	0.099				−0.071	−0.110	−0.176	0.036
Firm, Comp.	0.099					−0.039	−0.104	0.108
Firm, Fin. expert	0.099						−0.065	0.147
Firm, Board	0.100							0.212
Firm, All govern.	0.098							
2015	**Error**	**Firm**	**Firm, Inst. hold.**	**Firm, Anti-takeover**	**Firm, Comp.**	**Firm, Fin. expert**	**Firm, Board**	**Firm, All govern.**
Base model	0.181	16.018***	16.170***	16.134***	15.905***	15.887***	15.968***	16.025***
Firm	0.085		0.224	0.193	−0.157	−0.198	−0.074	0.031
Firm, Inst. hold.	0.084			−0.030	−0.381	−0.422	−0.298	−0.192
Firm, Anti-takeover	0.084				−0.350	−0.390	−0.267	−0.161
Firm, Comp.	0.086					−0.040	0.083	0.188
Firm, Fin. expert	0.086						0.124	0.228
Firm, Board	0.085							0.105
Firm, All govern.	0.085							
2016	**Error**	**Firm**	**Firm, Inst. hold.**	**Firm, Anti-takeover**	**Firm, Comp.**	**Firm, Fin. expert**	**Firm, Board**	**Firm, All govern.**
Base model	0.183	13.922***	13.984***	13.953***	13.986***	13.907***	13.922***	14.038***
Firm	0.089		0.044	0.028	0.040	−0.024	−0.048	0.086
Firm, Inst. hold.	0.089			−0.016	−0.004	−0.068	−0.092	0.042
Firm, Anti-takeover	0.089				0.012	−0.052	−0.076	0.058
Firm, Comp.	0.089					−0.064	−0.088	0.046
Firm, Fin. expert	0.089						−0.024	0.110
Firm, Board	0.089							0.135
Firm, All govern.	0.088							

Table 5: —*Continued*

Panel B: Return on assets, adj. $t+3$

2014	Error	Firm	Firm, Inst. hold.	Firm, Anti-takeover	Firm, Comp.	Firm, Fin. expert	Firm, Board	Firm, All govern.
Base model	0.177	10.882***	11.048***	10.877***	10.893***	10.846***	11.096***	11.409***
Firm	0.113		0.152	−0.006	−0.055	−0.063	0.185	0.412
Firm, Inst. hold.	0.112			−0.158	−0.210	−0.216	0.032	0.258
Firm, Anti-takeover	0.113				−0.049	−0.057	0.191	0.418
Firm, Comp.	0.113					−0.009	0.242	0.475
Firm, Fin. expert	0.113						0.249	0.479
Firm, Board	0.112							0.226
Firm, All govern.	0.111							
2015	**Error**	**Firm**	**Firm, Inst. hold.**	**Firm, Anti-takeover**	**Firm, Comp.**	**Firm, Fin. expert**	**Firm, Board**	**Firm, All govern.**
Base model	0.181	10.376***	10.637***	10.315***	10.778***	10.419***	11.049***	11.056***
Firm	0.116		0.285	−0.050	0.511	0.045	0.792	0.855
Firm, Inst. hold.	0.114			−0.334	0.230	−0.240	0.510	0.577
Firm, Anti-takeover	0.116				0.559	0.095	0.838	0.901
Firm, Comp.	0.113					−0.467	0.274	0.343
Firm, Fin. expert	0.115						0.747	0.811
Firm, Board	0.111							0.072
Firm, All govern.	0.111							
2016	**Error**	**Firm**	**Firm, Inst. hold.**	**Firm, Anti-takeover**	**Firm, Comp.**	**Firm, Fin. expert**	**Firm, Board**	**Firm, All govern.**
Base model	0.173	9.276***	9.390***	9.283***	9.651***	9.230***	9.452***	10.064***
Firm	0.109		0.088	0.009	0.274	−0.036	0.141	0.659
Firm, Inst. hold.	0.109			−0.078	0.187	−0.124	0.054	0.573
Firm, Anti-takeover	0.109				0.265	−0.045	0.132	0.649
Firm, Comp.	0.107					−0.311	−0.132	0.392
Firm, Fin. expert	0.109						0.177	0.695
Firm, Board	0.108							0.519
Firm, All govern.	0.105							

Table 6: **Mean out-of-sample errors and t-statistics for operating performance: Firm characteristics vs governance characteristics**

This table reports mean out-of-sample test errors in the first column and t-statistics for the differences in these errors. With t-statistics, we compare the model in the column to the model in the corresponding row. *Base model* denotes an uninformed baseline that uses an average outcome in the estimation data for prediction. *Firm* denotes firm characteristics. *Inst. hold.* denotes institutional investor holdings. *Anti-takeover* denotes anti-takeover provisions. *Comp.* denotes executive compensation. *Fin. expert* denotes board's financial expertise. *Board* denotes board characteristics. *All govern.* denotes all governance characteristics that is the union of *Inst. hold.*, *Anti-takeover*, *Comp.*, *Fin. expert*, and *Board*.

Panel A: Return on assets, adj. $t+1$

2014	Error	Firm	Inst. hold.	Anti-takeover	Comp.	Fin. expert	Board	All govern.
Base model	0.181	13.662***	1.689*	0.239	3.621***	0.476	3.448***	5.536***
Firm	0.099		−12.866***	−13.592***	−11.436***	−13.496***	−11.643***	−9.911***
Inst. hold.	0.172			−1.455	1.998**	−1.221	1.813*	4.010***
Anti-takeover	0.180				3.402***	0.237	3.228***	5.338***
Comp.	0.161					−3.180***	−0.193	2.040**
Fin. expert	0.178						3.003***	5.132***
Board	0.162							2.242**
All govern.	0.151							
2015	**Error**	**Firm**	**Inst. hold.**	**Anti-takeover**	**Comp.**	**Fin. expert**	**Board**	**All govern.**
Base model	0.181	16.018***	1.730*	0.202	4.071***	0.656	3.538***	5.827***
Firm	0.085		−15.748***	−16.019***	−14.165***	−15.951***	−14.408***	−12.650***
Inst. hold.	0.171			−1.532	2.458**	−1.082	1.900*	4.343***
Anti-takeover	0.180				3.892***	0.454	3.355***	5.667***
Comp.	0.159					−3.474***	−0.550	1.932*
Fin. expert	0.177						2.930***	5.284***
Board	0.162							2.462**
All govern.	0.149							
2016	**Error**	**Firm**	**Inst. hold.**	**Anti-takeover**	**Comp.**	**Fin. expert**	**Board**	**All govern.**
Base model	0.183	13.922***	1.641	0.260	3.872***	0.696	3.762***	5.569***
Firm	0.089		−13.360***	−13.855***	−11.997***	−13.726***	−11.883***	−10.566***
Inst. hold.	0.173			−1.385	2.320**	−0.953	2.213**	4.134***
Anti-takeover	0.182				3.635***	0.436	3.524***	5.354***
Comp.	0.160					−3.231***	−0.087	1.887*
Fin. expert	0.179						3.121***	4.984***
Board	0.161							1.950*
All govern.	0.150							

Table 6: —*Continued*

Panel B: Return on assets, adj. $t+3$

2014	Error	Firm	Inst. hold.	Anti-takeover	Comp.	Fin. expert	Board	All govern.
Base model	0.177	10.882***	1.422	0.300	3.143***	0.535	3.533***	5.183***
Firm	0.113		−10.093***	−10.718***	−8.700***	−10.654***	−8.473***	−7.044***
Inst. hold.	0.169			−1.123	1.778*	−0.895	2.177**	3.913***
Anti-takeover	0.175				2.858***	0.234	3.250***	4.919***
Comp.	0.159					−2.649***	0.391	2.154**
Fin. expert	0.174						3.044***	4.739***
Board	0.157							1.781*
All govern.	0.148							
2015	**Error**	**Firm**	**Inst. hold.**	**Anti-takeover**	**Comp.**	**Fin. expert**	**Board**	**All govern.**
Base model	0.181	10.376***	1.285	0.255	2.916***	0.541	3.135***	4.599***
Firm	0.116		−9.804***	−10.269***	−8.531***	−10.158***	−8.413***	−7.059***
Inst. hold.	0.173			−1.032	1.699*	−0.748	1.925*	3.482***
Anti-takeover	0.179				2.679***	0.286	2.899***	4.383***
Comp.	0.163					−2.413**	0.221	1.817*
Fin. expert	0.178						2.635***	4.142***
Board	0.162							1.608
All govern.	0.154							
2016	**Error**	**Firm**	**Inst. hold.**	**Anti-takeover**	**Comp.**	**Fin. expert**	**Board**	**All govern.**
Base model	0.173	9.276***	0.977	0.256	2.799***	0.438	2.437**	4.415***
Firm	0.109		−8.888***	−9.160***	−7.466***	−9.091***	−7.774***	−6.084***
Inst. hold.	0.167			−0.721	1.898*	−0.540	1.518	3.613***
Anti-takeover	0.171				2.561**	0.182	2.195**	4.201***
Comp.	0.155					−2.395**	−0.386	1.755*
Fin. expert	0.170						2.026**	4.054***
Board	0.158							2.139**
All govern.	0.146							

Table 7: **Mean out-of-sample errors and t-statistics for S&P credit rating: Firm characteristics vs firm and governance characteristics**

This table reports mean out-of-sample test errors in the first column and t-statistics for the differences in these errors. With t-statistics, we compare the model in the column to the model in the corresponding row. *Base model* denotes an uninformed baseline that uses an average outcome in the estimation data for prediction. *Firm* denotes firm characteristics. *Inst. hold.* denotes institutional investor holdings. *Anti-takeover* denotes anti-takeover provisions. *Comp.* denotes executive compensation. *Fin. expert* denotes board's financial expertise. *Board* denotes board characteristics. *All govern.* denotes all governance characteristics that is the union of *Inst. hold.*, *Anti-takeover*, *Comp.*, *Fin. expert*, and *Board*.

Panel A: S&P credit rating $t+1$

2014	Error	Firm	Firm, Inst. hold.	Firm, Anti-takeover	Firm, Comp.	Firm, Fin. expert	Firm, Board	Firm, All govern.
Base model	1.041	19.538***	20.350***	20.524***	21.485***	20.576***	22.574***	23.230***
Firm	0.541		1.050	1.372	2.498**	1.456	4.360***	5.280***
Firm, Inst. hold.	0.519			0.336	1.440	0.422	3.364***	4.288***
Firm, Anti-takeover	0.512				1.078	0.086	2.990***	3.892***
Firm, Comp.	0.490					−0.987	2.056**	3.005***
Firm, Fin. expert	0.510						2.900***	3.797***
Firm, Board	0.451							0.841
Firm, All govern.	0.435							
2015	**Error**	**Firm**	**Firm, Inst. hold.**	**Firm, Anti-takeover**	**Firm, Comp.**	**Firm, Fin. expert**	**Firm, Board**	**Firm, All govern.**
Base model	1.074	19.081***	19.511***	19.717***	19.989***	19.923***	20.792***	21.125***
Firm	0.509		0.853	1.196	1.844*	1.482	3.428***	4.229***
Firm, Inst. hold.	0.492			0.333	0.994	0.601	2.565**	3.382***
Firm, Anti-takeover	0.485				0.674	0.264	2.260**	3.093***
Firm, Comp.	0.471					−0.430	1.546	2.378**
Firm, Fin. expert	0.479						2.052**	2.911***
Firm, Board	0.438							0.882
Firm, All govern.	0.419							
2016	**Error**	**Firm**	**Firm, Inst. hold.**	**Firm, Anti-takeover**	**Firm, Comp.**	**Firm, Fin. expert**	**Firm, Board**	**Firm, All govern.**
Base model	1.037	17.989***	18.268***	18.585***	18.658***	18.663***	19.871***	19.825***
Firm	0.477		0.532	1.339	1.545	1.326	4.389***	4.340***
Firm, Inst. hold.	0.467			0.829	1.041	0.796	3.932***	3.891***
Firm, Anti-takeover	0.451				0.216	−0.067	3.019***	3.006***
Firm, Comp.	0.447					−0.291	2.767***	2.762***
Firm, Fin. expert	0.452						3.251***	3.225***
Firm, Board	0.395							0.091
Firm, All govern.	0.393							

Table 7: —*Continued*

Panel B: S&P credit rating $t + 3$

2012	Error	Firm	Firm, Inst. hold.	Firm, Anti-takeover	Firm, Comp.	Firm, Fin. expert	Firm, Board	Firm, All govern.
Base model	1.050	19.069***	19.138***	19.353***	19.546***	19.763***	20.081***	20.395***
Firm	0.501		0.175	0.544	1.049	1.044	2.038**	2.577**
Firm, Inst. hold.	0.498			0.366	0.872	0.856	1.855*	2.389**
Firm, Anti-takeover	0.490				0.514	0.479	1.501	2.034**
Firm, Comp.	0.478					−0.065	0.966	1.484
Firm, Fin. expert	0.479						1.088	1.639
Firm, Board	0.456							0.510
Firm, All govern.	0.444							
2013	**Error**	**Firm**	**Firm, Inst. hold.**	**Firm, Anti-takeover**	**Firm, Comp.**	**Firm, Fin. expert**	**Firm, Board**	**Firm, All govern.**
Base model	1.080	14.957***	15.354***	15.606***	16.377***	15.571***	16.750***	17.258***
Firm	0.604		0.559	0.917	1.981**	0.854	2.602***	3.326***
Firm, Inst. hold.	0.589			0.358	1.418	0.294	2.047**	2.768***
Firm, Anti-takeover	0.580				1.057	−0.065	1.690*	2.408**
Firm, Comp.	0.553					−1.125	0.654	1.374
Firm, Fin. expert	0.582						1.759*	2.480**
Firm, Board	0.537							0.702
Firm, All govern.	0.519							
2014	**Error**	**Firm**	**Firm, Inst. hold.**	**Firm, Anti-takeover**	**Firm, Comp.**	**Firm, Fin. expert**	**Firm, Board**	**Firm, All govern.**
Base model	1.032	15.462***	16.129***	16.046***	16.902***	16.335***	18.038***	18.383***
Firm	0.549		1.108	1.065	2.489**	1.516	4.645***	5.397***
Firm, Inst. hold.	0.524			−0.024	1.392	0.421	3.568***	4.348***
Firm, Anti-takeover	0.525				1.387	0.436	3.505***	4.263***
Firm, Comp.	0.494					−0.958	2.173**	2.983***
Firm, Fin. expert	0.515						3.106***	3.883***
Firm, Board	0.450							0.877
Firm, All govern.	0.433							

Table 8: **Mean out-of-sample errors and t-statistics for S&P credit rating: Firm characteristics vs governance characteristics**

This table reports mean out-of-sample test errors in the first column and t-statistics for the differences in these errors. With t-statistics, we compare the model in the column to the model in the corresponding row. *Base model* denotes an uninformed baseline that uses an average outcome in the estimation data for prediction. *Firm* denotes firm characteristics. *Inst. hold.* denotes institutional investor holdings. *Anti-takeover* denotes anti-takeover provisions. *Comp.* denotes executive compensation. *Fin. expert* denotes board's financial expertise. *Board* denotes board characteristics. *All govern.* denotes all governance characteristics that is the union of *Inst. hold.*, *Anti-takeover*, *Comp.*, *Fin. expert*, and *Board*.

Panel A: S&P credit rating $t + 1$

2014	Error	Firm	Inst. hold.	Anti-takeover	Comp.	Fin. expert	Board	All govern.
Base model	1.041	19.538***	4.715***	1.725*	13.819***	5.534***	15.672***	19.155***
Firm	0.541		−15.446***	−17.259***	−6.866***	−14.164***	−4.662***	−1.234
Inst. hold.	0.923			−2.869***	9.329***	0.906	11.302***	14.976***
Anti-takeover	0.996				11.707***	3.696***	13.514***	16.841***
Comp.	0.696					−8.208***	2.190**	6.083***
Fin. expert	0.900						10.136***	13.672***
Board	0.646							3.770***
All govern.	0.566							
2015	**Error**	**Firm**	**Inst. hold.**	**Anti-takeover**	**Comp.**	**Fin. expert**	**Board**	**All govern.**
Base model	1.074	19.081***	4.561***	1.572	15.012***	4.872***	15.217***	18.620***
Firm	0.509		−16.308***	−16.903***	−6.692***	−15.325***	−5.900***	−1.557
Inst. hold.	0.945			−2.821***	11.459***	0.415	11.713***	15.758***
Anti-takeover	1.026				12.928***	3.153***	13.147***	16.420***
Comp.	0.651					−10.663***	0.542	5.657***
Fin. expert	0.933						10.922***	14.769***
Board	0.639							4.858***
All govern.	0.539							
2016	**Error**	**Firm**	**Inst. hold.**	**Anti-takeover**	**Comp.**	**Fin. expert**	**Board**	**All govern.**
Base model	1.037	17.989***	3.332***	1.767*	12.603***	4.490***	13.751***	16.555***
Firm	0.477		−15.314***	−16.106***	−8.015***	−14.765***	−6.419***	−2.745***
Inst. hold.	0.935			−1.518	9.474***	1.131	10.709***	13.734***
Anti-takeover	0.982				10.678***	2.643***	11.836***	14.651***
Comp.	0.661					−8.574***	1.598	5.616***
Fin. expert	0.901						9.873***	13.077***
Board	0.623							3.976***
All govern.	0.532							

Table 8: —*Continued*

Panel B: S&P credit rating $t + 3$

2012	Error	Firm	Inst. hold.	Anti-takeover	Comp.	Fin. expert	Board	All govern.
Base model	1.050	19.069***	3.930***	1.359	12.815***	4.132***	15.027***	16.917***
Firm	0.501		−15.465***	−17.431***	−7.891***	−14.799***	−5.163***	−3.445***
Inst. hold.	0.939			−2.523**	8.911***	0.260	11.223***	13.161***
Anti-takeover	1.012				11.251***	2.742***	13.444***	15.289***
Comp.	0.693					−8.449***	2.709***	4.868***
Fin. expert	0.931						10.700***	12.564***
Board	0.625							2.047**
All govern.	0.576							
2013	**Error**	**Firm**	**Inst. hold.**	**Anti-takeover**	**Comp.**	**Fin. expert**	**Board**	**All govern.**
Base model	1.080	14.957***	3.491***	1.272	9.793***	4.067***	11.411***	13.797***
Firm	0.604		−12.351***	−13.325***	−5.978***	−11.548***	−3.985***	−1.655*
Inst. hold.	0.971			−2.118**	6.666***	0.634	8.438***	11.040***
Anti-takeover	1.039				8.289***	2.695***	9.881***	12.184***
Comp.	0.772					−5.950***	1.904*	4.494***
Fin. expert	0.952						7.705***	10.250***
Board	0.716							2.486**
All govern.	0.647							
2014	**Error**	**Firm**	**Inst. hold.**	**Anti-takeover**	**Comp.**	**Fin. expert**	**Board**	**All govern.**
Base model	1.032	15.462***	2.986***	1.623	10.490***	3.698***	12.577***	14.404***
Firm	0.549		−13.080***	−13.670***	−6.680***	−12.300***	−3.958***	−1.627
Inst. hold.	0.939			−1.308	7.698***	0.739	9.943***	11.919***
Anti-takeover	0.980				8.694***	2.019**	10.786***	12.607***
Comp.	0.714					−6.904***	2.713***	5.144***
Fin. expert	0.916						9.156***	11.132***
Board	0.644							2.396**
All govern.	0.586							

Table 9: **Instrumental variable estimation for audit committee independence**

This table replicates the main result in Duchin et al. (2010) as reproduced by Atanasov and Black (2021) using data from Duchin et al. (2010). These are the estimates from regressing firm performance during 2000–2005 on the change in the percentage of independent directors. The columns correspond to columns (1), (2), (5), (6), (7) of Table 2 in Atanasov and Black (2021). Columns (1) and (2) report the first-stage results using *Noncomply dummy* and *Noncomply dummy* × *InfoCost* as instruments for Δ*Indep* and Δ*Indep* × *InfoCost*. Columns (5)–(7) report the second-stage results. Reported first-stage regressions are for sample with Δ*ln(Q)* as an outcome variable. *Noncomply dummy* is a dummy for a firm being not in compliance with SOX in 2000, using data from 2000. *InfoCost* is an information cost index that averages a firm's percentile ranking in the sample according to the number of analysts who posted forecasts about the firm in a given year (the reverse ranking is used), the dispersion of analyst forecasts (i.e., the standard deviation of earnings forecasts across analysts prior to a quarterly earnings announcement, normalized by the firm's total book assets and averaged across four quarters in a given year), and the analyst forecast error (i.e., the absolute difference between the mean analyst earnings forecast prior to a quarterly earnings announcement and the actual earnings, normalized by the firm's total book assets and averaged across four quarters in a given year). The index is scaled to range from zero (low) to one (high). *Board size* is the number of directors on the board. *Book leverage* is debt divided by book assets. *Age* is the number of years since the firm's first appearance on Compustat with valid asset data. *Market cap* is the logarithm of the market value of equity. *Indep* is the percentage of independent directors. Δ*Indep* is the change in *Indep* between fiscal years 2000 and 2005, i.e., Δ*Indep* = $Indep_{2005}$ - $Indep_{2000}$. Δ*ROA* is the change in return on assets (%) between fiscal years 2000 and 2005. Δ*ln(Q)* is the change in the logarithm of Tobin's Q between fiscal years 2000 and 2005. *Mean return* is the average monthly returns (%) from the end of fiscal year 2000 to the end of fiscal year 2005. All variables are winsorized at the 1st and 99th percentiles. All regressions include 48 Fama-French industry dummies. The standard errors, with industry clusters, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	ΔIndep (1)	ΔIndep × InfoCost (2)	ΔROA (3)	Δln(Q) (4)	Mean return (5)
Noncomply dummy	10.490***	−0.299			
	(3.160)	(1.360)			
InfoCost	−4.025	3.480	−0.914	−28.171*	0.049
	(4.486)	(2.393)	(3.194)	(15.140)	(0.464)
Board size	−0.127	−0.122	−0.039	1.060	−0.014
	(0.194)	(0.100)	(0.146)	(0.723)	(0.020)
Book leverage	0.237	0.044	0.940**	4.835***	0.029
	(0.426)	(0.252)	(0.358)	(0.842)	(0.061)
Age	−0.073*	−0.015	0.021	0.617***	0.006
	(0.037)	(0.018)	(0.022)	(0.127)	(0.004)
Market cap	0.191	0.076	−0.456***	−15.263***	−0.390***
	(0.238)	(0.134)	(0.151)	(1.972)	(0.046)
Noncomply dummy × InfoCost	2.869	12.482***			
	(6.060)	(3.482)			
Instrumented Δ Indep			0.234*	1.025	0.063***
			(0.139)	(0.637)	(0.020)
Instrumented(ΔIndep × InfoCost)			−0.507*	−2.758**	−0.116***
			(0.300)	(1.305)	(0.041)
Observations	905	905	897	905	805
R^2	0.205	0.219	0.097	0.370	0.247
Adjusted R^2	0.155	0.170	0.040	0.331	0.195

Table 10: **Intention-to-treat effects**

This table presents intention-to-treat equivalents for columns (3)–(5) in Table 9. Reported first-stage regressions are for sample with $\Delta\, ln(Q)$ as an outcome variable. The variables are defined in Table 9. All regressions include 48 Fama-French industry dummies. The standard errors, with industry clusters, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	ΔROA (1)	Δln(Q) (2)	Mean return (3)
Board size	−0.004	1.266*	−0.005
	(0.137)	(0.723)	(0.020)
Book leverage	0.973***	4.956***	0.042
	(0.345)	(0.652)	(0.062)
Age	0.011	0.584***	0.003
	(0.021)	(0.142)	(0.003)
Market cap	−0.457***	−15.277***	−0.388***
	(0.144)	(2.176)	(0.049)
Noncomply dummy	2.573*	11.575*	0.613***
	(1.422)	(6.225)	(0.197)
InfoCost	−3.639*	−41.892***	−0.660**
	(2.112)	(8.435)	(0.279)
Noncomply dummy × InfoCost	−5.596*	−31.487**	−1.109**
	(2.973)	(12.144)	(0.420)
Observations	897	905	805
R^2	0.139	0.414	0.365
Adjusted R^2	0.085	0.378	0.321

Table 11: **Mean cross-validation errors**

This table reports mean cross-validation errors for the intention-to-treat analyses in Table 10. *Base MSE* is mean cross-validation error for the model that includes only 48 Fama-French industry dummies. *MSE without IV* is mean cross-validation error for the model that includes control variables, industry dummies, and *InfoCost*, i.e., *without* the exogenous shifter *Noncomply dummy* that is pre-SOX non-compliance with SOX. *MSE with IV* is mean cross-validation error for the model that adds the exogenous shifter *Noncomply dummy* to the model above. *MSE decrease* is the difference between *MSE without IV* and *MSE with IV*. *p-value* is p-value derived using randomization inference discussed in Section 6.

Y	Base MSE	MSE without IV	MSE with IV	MSE decrease	p-value
Δln(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