Contextual Corporate Governance†

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Abstract. This paper assesses the importance of context—both observed and unobserved—in shaping a firm's governance choices. We show that observed context predicts significant variation in out-of-sample governance choices. However, the impact of context is highly nonlinear and incorporating nonlinearities substantially improves predictive accuracy. We also propose a method to obtain information about unobserved context and show that utilizing the information further increases predictive accuracy. Moreover, we construct a new measure of governance quality, *context consistent governance* (*CCG*), which outperforms unconditional governance indices and highlights the value of integrating context into the measurement of corporate governance.

Keywords: Corporate governance, context, contextual factors, prediction, machine learning

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1. Introduction

A widely-voiced view among academics and practitioners is that corporate governance is context-specific and that one-size-fits-all governance recommendations are problematic (e.g., Adams et al., 2010; Armstrong et al., 2010). Despite this, existing measures of governance quality employed in the academic literature, including governance indices (e.g., G-Index, E-Index), typically do not incorporate contextual information. That is, these measures assert the efficacy of specific governance mechanisms, often weighted equally, without considering that different types of firms might require different governance structures. While this practice undoubtedly stems from its convenience in operationalizing measures of governance quality, incorporating contextual factors would seem a natural next step in extending these measures and our understanding of the way governance influences corporate decision-making. How does context matter for corporate governance? To what extent is governance-relevant context observed or unobserved? Can observed contextual information be leveraged to improve measures of governance quality? This paper develops a framework to address these questions.

Although the literature on corporate governance is extensive, the guidance it can provide for answering these questions is limited. Many papers examine how some aspect of a firm's governance affects its value or performance. However, for identification, these studies typically attempt to abstract away from context by seeking situations where a firm's governance structure (or a shock to this structure) is plausibly exogenous. While certain studies have documented associations between various firm characteristics and governance mechanisms, these studies are not designed to assess the potential nonlinear effects of context on governance choices, the extent of unobserved context, or how context can be used in measuring governance quality.

In this paper, we develop a prediction-based approach to investigate how context shapes a firm's governance choices. Drawing from prior theoretical and empirical literature, we begin by formulating a linear prediction model that incorporates observed context and use the model to examine how well observed contextual factors predict governance choices in out-of-sample data.[1] The four observed contextual factors that we identify and include in the model are: the firm's *life cycle*, *nature of investments*, *operational complexity*, and *information environment*. For example, theory suggests that the benefits and costs of anti-takeover provisions may change over a firm's life cycle (e.g., Kim and Michaely, 2019; Johnson et al., 2022). Importantly, our prediction model can support (or undermine) the existence of a causal relation between observed context and governance choices without specifying an identification strategy, because prediction is a necessary (though not sufficient) condition for causality (Watts, 2014; Gow et al., 2023).

We show that observed context predicts substantial out-of-sample variation in governance choices.[2] Compared to a base model with no context (i.e., the unconditional model), the linear prediction model with observed context leads to a statistically significant increase in predictive accuracy for seven of the ten governance mechanisms. While all observed contextual factors improve predictive accuracy to some degree, the life cycle and operational complexity factors are especially important, leading to statistically significant improvements in predictive accuracy for four and five of the ten governance mechanisms, respectively. Averaged across all governance mechanisms, the linear prediction model with observed context improves predictive accuracy by 18%. Because prediction is a necessary condition for causality, our findings with out-of-sample

[1] The linear model has been the workhorse model in the empirical literature to examine the relations between firm characteristics and governance mechanisms (e.g., Linck et al., 2008; Johnson et al., 2022). It provides a benchmark for our subsequent analysis in which we incorporate nonlinearities and unobserved context into the prediction model.
[2] We analyze ten governance mechanisms that firms may choose: staggered boards, poison pills, unequal voting rights, limits to amend bylaws, limits to amend charter, limits to approve mergers, board size, board independence, board cooption, and CEO duality.

predictive accuracy are consistent with a causal relation between the observed context and governance choices, confirming the commonly-held view that observed context matters for governance structure.

Next, we examine two potential improvements to the linear prediction model. First, observed context could have nonlinear effects on governance choices. For example, the information environment may play an especially vital role in young firms where there is relatively higher information asymmetry.[3] To quantify the improvement from including nonlinearities, we build on the notion of *model completeness* developed in Fudenberg, Kleinberg, Liang, and Mullainathan (2022), henceforth FKLM. Model completeness compares the prediction error of the linear prediction model to the lowest possible prediction error that is achievable given the observed contextual factors, which FKLM term as *irreducible error*. Following FKLM, we estimate irreducible error using the predictions from the random-forest algorithm, a machine-learning method that aggregates the predictions from multiple decision trees. Averaged across all governance mechanisms, we show that the linear prediction model's completeness is 0.32, indicating that of the total variation in governance choices that could possibly be predicted by the observed contextual factors (i.e., *predictable variation*), the linear prediction model predicts 32% with the remaining 68% captured by nonlinearities. This suggests that nonlinearities are highly important for understanding the role of context in influencing governance choices.[4]

Second, there could be unobserved context (e.g., the CEO's preferences) that matters for governance choices. While prior empirical studies commonly account for unobserved context

[3] Consistent with this, Field and Lowry (2022) show that the increase in classified boards among IPO firms is concentrated among firms with high information asymmetry.

[4] Notice that by definition, model completeness is measured for the given observed contextual factors in the prediction model. As we show next, predictive accuracy can be further improved by including unobserved context—outside of the observed contextual factors—in the prediction model.

through the use of firm fixed effects, this approach is not feasible in our prediction setting because there are firms in the out-of-sample data that do not belong in the training sample. To overcome this challenge, we use a machine-learning method, the k-modes clustering algorithm, to obtain information about unobserved context. This algorithm groups firms with similar governance structures together in clusters *without using the observed contextual factors*; therefore, the clusters that emerge from this algorithm provide additional information about unobserved context that can potentially enhance the prediction model (Chaturvedi et al., 2001).[5] Averaged across all governance mechanisms, we show that including information from these clusters substantially improves on the prediction model with observed context and nonlinearities, increasing predictive accuracy by 27%. This suggests that unsupervised machine-learning algorithms like k-modes clustering can offer insights into unobserved context, enhancing our ability to explain out-of-sample variation in corporate governance choices.

One of the main challenges in corporate governance research is measuring a firm's governance quality. Many prior studies measure governance quality through indices, which involve the linear aggregation of distinct governance mechanisms that are categorized as being unconditionally strong or weak (see Table 1 for more information). Other studies use simpler and possibly more interpretable measures, such as the proportion of independent directors. However, few studies account for contextual information in the measurement of governance quality. We address this gap by constructing a new measure of governance quality, *context consistent governance* (*CCG*), which captures how close a firm's actual governance structure is to the one predicted by its observed contextual factors.

[5] In other words, the clusters that emerge from the k-modes clustering algorithm capture latent variables that affect governance choices.

We find that *CCG* is positively associated with out-of-sample firm value and operating performance: a one standard deviation increase in *CCG* is associated with a 0.12 (0.06) standard deviation increase in *Firm Value*$_{t+1}$ (*Operating Performance*$_{t+1}$), indicating that observed context can be useful for identifying well-governed firms. Comparing *CCG* to unconditional governance indices, we find that *CCG* has stronger associations with out-of-sample firm outcomes (with and without additional control variables), suggesting that incorporating contextual information can improve the measurement of governance quality.

Our paper contributes to the literature on corporate governance in several ways. First, it provides new evidence on the existence and strength of causal relations between observed contextual factors and corporate governance mechanisms using a prediction-based approach.[6] These relations are important because they are often the focus of corporate governance theory and help us understand why firms make the governance choices they do. Across a variety of governance mechanisms, we show that observed contextual factors—especially the life cycle and operational complexity factors—improve predictive accuracy.

Second, we provide estimates of completeness for the linear model that has been the workhorse model in the empirical literature to examine the relations between firm characteristics and governance mechanisms. We show that the linear model is highly incomplete and could be substantially improved by incorporating the nonlinear effects of contexts on governance choices.

Third, we contribute to the measurement of corporate governance by developing and evaluating a context-specific measure of governance quality: *context consistent governance*

[6] While a prediction result suggests a causal relation only in the sense of a necessary condition, it sidesteps the need for a proper identification condition that is often hard to satisfy.

(*CCG*). Our results highlight the value of incorporating contextual information into the measurement of corporate governance.[7]

2. Governance Choices and Observed Contextual Factors

2.1. Governance Choices

While there are numerous governance mechanisms, our objective is to focus on firm governance choices that have been studied extensively in the academic literature. Towards this objective, we search accounting and finance journals (JAE, JAR, TAR, JFE, JF, and RFS) over the five-year period 2016–2020 and identify all papers that employ some measure of governance quality in their empirical analyses. Table 1 presents our descriptive findings and shows that 210 papers in total have an empirical proxy for governance quality, with the papers split roughly evenly between accounting and financial journals. Among these papers, 57% employ a governance index, with either the G-Index or E-Index being used in about two thirds of them. Other common measures used to proxy for governance quality include board independence (44% of papers), board size (30%), and CEO duality (27%).

Based on our descriptive findings in Table 1, we examine two broad classes of governance choices: antitakeover provisions and board characteristics. Antitakeover provisions pertain to different ways in which managers are protected from removal. By preventing or hindering the threat of removal, these provisions allow greater opportunities for shirking, empire-building, and the extraction of private benefits by managers. Meanwhile, board characteristics refer to features of the board that can impact the board's effectiveness at monitoring or advising management.

[7] Our prediction framework highlights the value of prediction methods utilizing machine-learning algorithms in corporate governance research and complement the findings in Erel et al. (2021), which suggest that machine-learning methods can assist firms in their director nomination decisions.

For antitakeover provisions, we include six indicators that feature prominently in the G-Index first constructed by Gompers et al. (2003) and the E-Index first constructed by Bebchuk et al. (2009): staggered boards, poison pills, unequal voting rights, supermajority requirements to amend bylaws, supermajority requirements to amend the charter, and supermajority requirements to approve mergers. Staggered boards divide directors into classes, typically three, with only one class of directors coming up for election each year. As a result, shareholders cannot replace a majority of the directors in any given year, which makes staggered boards a powerful defense against a proxy fight or proxy contest. Poison pills entitle non-bidder shareholders to a special right, such as the right to purchase additional shares at a discount, in the event of an unsolicited takeover offer. Hence, they deter unsolicited takeovers that would result in the removal of incumbents. Unequal voting rights give certain shareholders (typically insiders or founding members) greater voting rights and can protect the firm from potential takeovers. Supermajority requirements for bylaw or charter amendments make it more difficult for shareholders to remove defensive antitakeover provisions that management placed earlier in the bylaws or charter. Finally, supermajority requirements to approve mergers can deter bidding by a hostile bidder by making it easier for insider shareholders to defeat a merger attempt. The above antitakeover provisions capture an important and widely-researched aspect of corporate governance, namely the insulation of incumbent managers from removal.

For board characteristics, we examine board size, board independence, board cooption, and CEO duality. Board size is the number of directors and is an important dimension of board structure because a larger board may be able to provide more valuable advice to the CEO but at the expense of coordination problems and director free-riding. Board independence is the proportion of independent non-executive directors on the board. An independent board is commonly viewed as necessary for effective monitoring of management. In recent years, due to regulations that require a majority of the board be independent, the proportion of independent non-executive directors on boards has increased significantly and varies less across firms. As an alternative to board independence, board cooption is the proportion of directors appointed after the CEO assumes office (Coles et al., 2014). Finally, CEO duality refers to the situation where the CEO is also the chairman of the board. When the CEO is also the chairman, it may be more difficult for the board to provide effective oversight and hold the CEO accountable.

2.2. Observed Contextual Factors

In this section, we introduce the contextual factors that we focus on in our analysis. Our objective is to find contextual factors that may be relevant for a variety of governance choices. For this, we turn to prior theoretical and empirical literature on the economic determinants of corporate governance and its effectiveness, identifying four broad constructs. We discuss these constructs below and how we operationalize them. Note that these observed contextual factors are not intended to be exhaustive; it is very possible—and likely—that there are other contextual factors that influence a firm's governance choices beyond the ones we are considering. Part of our analysis will be determining to what extent other—possibly unobserved—contextual factors matter.

Observed Contextual Factor #1 – Life Cycle: Prior literature suggests that the benefits and costs of governance mechanisms may change over a firm's life cycle. Kim and Michaely (2019) argue that young firms have lower agency costs associated with dual-class shares because insiders typically have strong ownership incentives to maximize firm value, the innovation and growth opportunities of a firm are tied to founder-managers, and outside investors are less knowledgeable about the investment opportunities than insiders are. Johnson et al. (2022) show that the average relation between firm value and the use of takeover defenses is positive at the IPO but declines and becomes negative as a firm matures. Field and Lowry (2022) show that while the percentage of mature firms with classified boards or dual class shares has declined since 1990, the percentage of newly public firms with these structures has increased over the period. Karpoff and Wittry (2022) survey the literature on takeover defenses and suggests that researchers can use firm age or measures of firm maturity to account for the heterogeneous effects of takeover defenses on firm value. To operationalize a firm's life cycle, we use two different empirical proxies. First, we use the natural log of one plus the number of years that the firm has been listed on Compustat. Second, we construct an indicator variable equal to one if the firm is a mature or decline one according to cash-flow patterns developed in Dickinson (2011).

Observed Contextual Factor #2 – Nature of Investments: Prior literature suggests that firms with high long-term investment face a different set of governance challenges than firms with low long-term investment. Stein (1988) argues that firms with high long-term investment may face high takeover pressure because of temporarily low current profits, which may be damaging in the long term and can benefit from implementing antitakeover provisions like staggered boards or poison polls. Cremers et al. (2017) show that for firms with high long-term investment, as measured by R&D expenditures, a staggered board is associated with higher firm value, contradicting the common (unconditional) view that staggered boards entrench managers and are associated with lower value. Coles et al. (2008) argue that the firm-specific knowledge of insiders is especially important at firms with high R&D investment and find that firms with high R&D investment have a higher fraction of insider directors.

The literature also suggests that the need for certain governance mechanisms varies with the firm's reliance on relationship investment. As argued by Knoeber (1986), firms that make high relationship investments may benefit from takeover defenses because they allow a firm to commit to a business strategy that cannot be easily reversed through an outside takeover. Cremers et al. (2017) show that for firms with high relationship investment, a staggered board is associated with higher firm value. Johnson et al. (2015) show that IPO firms deploy more takeover defenses when they have important business relationships to protect. To operationalize a firm's long-term investment, we use a firm's R&D expenditure (Cremers et al., 2017). To operationalize a firm's relationship investment, we use the fraction of sales that are due to the firm's largest customer (Cremers et al., 2017).

Observed Contextual Factor #3 – Operational Complexity: Prior literature suggests that a firm's operational and organization complexity is an important economic determinant of a firm's governance structure. Linck et al. (2008) argue that larger firms with disparate businesses and more complex financial structures should benefit more from bringing in outsiders with a range of expertise, resulting in larger, more independent boards. Goergen et al. (2019) find that the stock market reaction to the disclosure of the most frequently stated reasons for combining the CEO and board chair roles depends on a firm's complexity and size as well as the competitiveness and dynamism of its business environment. We measure a firm's operational complexity using the combination of firm size, the proportion of debt in the capital structure, and the number of business segments (Coles et al., 2008; Linck et al., 2008; Reeb and Upadhyay, 2010).

Observed Contextual Factor #4 – Information Environment: Prior literature suggests that the firm's information environment is also an important economic determinant of a firm's governance structure. Cai et al. (2015) show that firms with greater information asymmetry rely less on shareholder-elected independent boards and more on market discipline and CEO incentives to monitor management. Adams and Ferreira (2007) model the tradeoff between monitoring and advising and find that a non-independent board may be optimal in the presence of information frictions. Ferreira et al. (2011) show that the information contained in stock prices affects the structure of corporate boards. To operationalize a firm's information environment, we use the number of analysts, analyst forecast dispersion, and analyst forecast errors (e.g., Cai et al., 2015).

3. Data

We obtain governance data from ISS Directors and ISS Governance. Our sample starts from 2007 because RiskMetrics changed its methodology for collecting governance data in 2007, making it difficult to compare governance data before and after 2007. Using Compustat, CRSP, and IBES, we construct proxies for the contextual factors and firm outcomes. Our final sample consists of 13,711 firm-year observations for the years between 2007 and 2021. All continuous variables are winsorized at the 1% and 99% levels. Table 2 reports descriptive statistics for the sample in three panels.

Panel A shows summary statistics for various antitakeover provisions. *Staggered Board* is an indicator variable equal to one if the firm has a board in which directors are divided into separate classes with each class being elected to overlapping terms. *Poison Pill* is an indicator variable equal to one if the firm has a shareholder right that is triggered in the event of an unauthorized change in control that renders the target company financially unattractive or dilutes the voting power of the acquirer. *Unequal Voting Rights* is an indicator variable equal to one if the firm has unequal voting rights across common shareholders. *Limits to Amend Bylaws* is an indicator variable equal to one if the firm has a provision limiting shareholders' ability through majority vote to amend the corporate bylaws. *Limits to Amend Charter* is an indicator variable equal to one if the firm has a provision limiting shareholders' ability through majority vote to amend the corporate charter. *Limits to Approve Mergers* is an indicator variable equal to one if the firm has a provision limiting shareholders' ability through majority vote to approve a merger. *Board Size* is the number of directors that sit on the board. *Antitakeover Index* is the sum of all antitakeover provisions. The mean (median) firm in our sample has 1.71 (2.00) antitakeover provisions.

Panel A also shows summary statistics for various board characteristics. For the purpose of classification in our subsequent prediction analysis, we construct binary indicators using the board characteristics. *High Board Size* is an indicator variable equal to one if the number of directors that sit on the board is above the median. *Low Board Independence* is an indicator variable equal to one if the proportion of independent non-executive directors on the board is below the median. *High Board Cooption* is an indicator variable equal to one if the proportion of directors appointed after the CEO assumes office is above the median. *CEO Duality* is an indicator variable equal to one if the CEO is also chairman of the board.

Panel A also shows summary statistics for the contextual variables and firm outcomes.[8] *Firm Age is* the natural log of the number of year that the firm has been listed on Compustat. *Operational Maturity* is an indicator variable equal to one if the firm is a mature or decline one according to cash-flow patterns developed in Dickinson (2011). *R&D Investment* is R&D expenditures scaled by total assets (if missing, set to zero). *Relationship Investment* is the fraction of total sales that are due to the firm's largest customer. *Firm Size* is the natural log of total assets. *Leverage* is short-term plus long-term debt scaled by total assets. *Number of Segments* is the number of business segments. *Number of Analysts* is the natural log of the number of analysts. *Analyst Forecast Dispersion* is the standard deviation annual earnings per share forecasts. *Analyst Forecast Error* is the absolute value of the difference between the actual and forecasted annual earnings per share. *Firm* $Value_{t+1}$ is the market value of assets scaled by the book value of assets in year $t+1$. The

[8] To be clear, "contextual factors" refer to the constructs *life cycle*, *nature of investments*, *operational complexity*, and *information environment*, while "contextual variables" refer to the proxies used to capture these constructs.

market value of assets is the book value of assets plus the market value of common stock less the sum of the book value of common stock. *Operating Performance*$_{t+1}$ is operating income before depreciation scaled by total assets in year *t+1*.

Panel B displays the correlations across governance mechanisms. With the exception of *Unequal Voting Rights*, the antitakeover provisions are positively correlated with one another. *CEO Duality* is positively correlated with *High Board Size*, positively correlated with *Low Board Independence*, and positively correlated with *High Board Cooption*. Panel C displays the correlations across the contextual variables. The correlations indicate that there may be overlap across the contextual variables. For example, *Firm Size* is positively associated with *Number of Analysts*. As we discuss below, this is not a major issue in our analysis since we are primarily interested in understanding the combined ability of all of the contextual factors in explaining a firm's governance choices.

4. Observed Context and Governance Choices

4.1. Research Design

In this section, we investigate to what extent observed context (i.e., the observed contextual factors described in Section 2) can predict out-of-sample governance choices. Before getting into the details of our research design, we first note why we are interested in predicting governance choices using observed context. As discussed in Section 2, there are many theoretical reasons to believe that a firm's governance choices are influenced by the observed contextual factors, such as the firm's *life cycle* or *information environment*. Examining out-of-sample predictive accuracy provides a way to assess the degree to which the empirical data supports the theory. For example, FKLM argue that the usefulness of economic models can be evaluated by testing the correctness of their predictions.

Moreover, studying out-of-sample predictive accuracy offers a way to assess the relation between observed context and governance mechanisms when providing direct coefficient estimates is not possible due to the lack of plausibly exogenous variation in a firm's observed contextual factors. This is possible because of the link between prediction and causation: if a relation between a contextual factor and a governance mechanism is causal, the contextual factor should help in the prediction of the governance mechanism. In other words, prediction is a necessary (though not sufficient) condition for causality (Gow et al., 2023). Supporting the view that prediction is a necessary condition for causality, Watts (2014) states that: "The claim that prediction is a necessary (but not sufficient) feature of causal explanation is consistent with a view of causality that is almost universally accepted by sociologists—even sociologists who have explicitly denied the necessity of prediction."

Therefore, we use the out-of-sample predictive accuracy of observed contextual factors for firms' governance choices to shed light on whether observed context matters for governance choices. Specifically, we formulate the following prediction problem. The outcome of interest Y is a binary governance mechanism (e.g., *Staggered Board*, *CEO Duality*), while features X are the observed contextual variables (e.g., *Firm Age*, *Number of Segments* etc.). A prediction rule is any function $f(\cdot)$ that uses the observed contextual variables C to estimate the likelihood of a governance mechanism Y. For our prediction rule $f(\cdot)$, we initially start with a linear functional form $f(\boldsymbol{c}) = \langle \boldsymbol{c}, \boldsymbol{\theta} \rangle$ where $\boldsymbol{c}$ are the observed contextual variables and $\boldsymbol{\theta}$ is a vector of weights applied to each contextual variable. The linear model has been the workhorse model in the empirical literature to examine the relations between firm characteristics and governance mechanisms (e.g., Linck et al., 2008; Johnson et al., 2022). Further, by using a linear functional form, we establish a benchmark for our subsequent analysis in Section 5 where we incorporate nonlinearities and unobserved context into the prediction model.

We use the following procedure to estimate the predictive accuracy of the linear model in out-of-sample data. First, we randomly divide the sample into a training dataset and a testing dataset. The training dataset consists of 80% of sample, while the testing dataset consists of the remaining 20% of sample.[9] Second, we estimate a logistic regression of governance mechanisms on the observed contextual variables using the training dataset to determine $\boldsymbol{\theta}$. Third, with the estimated model, we predict governance choices in the testing dataset and compute two widely-used measures of out-of-sample predictive accuracy: mean squared error (MSE) and the area under the receiver operating characteristic curve (AUC). MSE calculates the average squared error between the actual outcomes and the outcomes predicted by the model. AUC measures the prediction model's ability to discriminate between firms with and without a particular governance mechanism. Specifically, it quantifies the probability that a firm with a given governance mechanism will receive a higher predicted value from the model than a firm without the governance mechanism.[10] An AUC of 1.00 indicates perfect prediction, while an AUC of 0.50 is equivalent to random guessing. To enhance the readability of our findings, we present our results in terms of the complement of AUC, denoted by $\overline{\text{AUC}} = 1 - \text{AUC}$. Because predictive accuracy is higher when MSE and $\overline{\text{AUC}}$ are lower, we also refer to MSE and $\overline{\text{AUC}}$ as *prediction error*, with the understanding that lower prediction error is equivalent in meaning to higher predictive accuracy.

[9] In untabulated analyses, we consider alternative sample splitting procedures such as k-fold cross-validation or random firm splits. Our inferences are robust to these other procedures.
[10] Note that AUC only applies when the outcome is binary. All of the governance choices in our analysis are binary.

4.2. Results

Table 3 Panel A reports the MSEs obtained using the out-of-sample procedure described above. Consider first the case of staggered boards. The MSE under the base model (i.e., no observed context) is 0.244. When the *life cycle* contextual factor is included on its own in the linear prediction model, the MSE falls to 0.230. Similarly, when the *operational complexity* (*information environment*) contextual factor is included on its own in the linear prediction model, the MSE falls to 0.219 (0.233). Including all four contextual factors together in the linear prediction model, the MSE falls to 0.212. This is a decrease of 13% in MSE relative to the base model with no contextual factors. The t-statistic comparing the errors in the base model to the errors in the linear prediction model with all four contextual factors indicates that the reduction in MSE is statistically significant. Hence, these results indicate that observed context predicts significant out-of-sample variation in the use of staggered boards and suggests that observed context matters for the choice of whether or not to have a staggered board.

Examining across other governance mechanisms in Table 3 Panel A, we find that for the most part, the four contextual factors predict significant out-of-sample variation in other governance mechanisms as well. For example, *operational complexity* leads to a statistically significant decrease in prediction error for five of the ten governance mechanisms, while *life cycle* leads to an decrease in prediction error for four of the ten mechanisms. Averaged across all governance mechanisms, MSE decreases from 0.204 in the base model to 0.188 in the linear prediction model with all four contextual factors (a reduction of 8%). The largest reduction in MSE occurs when predicting *High Board Size*, decreasing from 0.249 in the base model to 0.169 in the linear prediction model with all contextual factors (a reduction of 32%).

Table 3 Panel B reports estimates of $\overline{\text{AUC}}$ for the linear prediction model. Averaged across all governance mechanisms, $\overline{\text{AUC}}$ decreases from 0.500 in the base model to 0.355 in the linear model with all four contextual factors (a decrease of 29%).[11] This means that the linear prediction model with all four contextual factors has a 64.5% probability ((1 – 0.355)*100) of correctly discriminating whether a firm would have a particular governance mechanism or not. In other words, the model has a 64.5% chance of assigning a higher predicted value to a firm with that specific governance mechanism than to a firm without it. Overall, the findings in Table 3 support the view that observed context has significant impact on governance choices.[12]

5. Model Completeness and Unobserved Context

5.1. Model Completeness

In the previous section, we used the linear prediction model to demonstrate that observed context matters for corporate governance and to provide a benchmark on the ability of observed context to predict governance choices. However, the linear model can be limited if observed context has nonlinear effects on governance choices. For example, the information environment could play an especially important role in younger firms where there is relatively higher information asymmetry. Consistent with this, Field and Lowry (2022) show that the increase in classified boards among IPO firms is concentrated among firms with high information asymmetry.

In this section, we investigate the extent to which the linear model could be improved by incorporating nonlinearities, using the measure of *model completeness* developed by FKLM.

[11] Including observed context results in a more pronounced improvement in predictive accuracy with $\overline{\text{AUC}}$ than with MSE due to the binary nature of the outcome variables.

[12] Taking the midpoint of the MSE and $\overline{\text{AUC}}$ estimates, the linear model with all four contextual factors decreases prediction error by about 18% ((8% + 29%)/2).

Before discussing model completeness, it is necessary to first understand the notion of *irreducible error*. FKLM define irreducible error as the lowest possible prediction error that is achievable for a given set of features. In our setting, irreducible error is the prediction error of a model that uses the information from a given set of contextual factors in the "best" way in order to capture regularities in governance choices.[13]

With this understanding and following FKLM, model completeness compares the performance of our linear prediction model to that of the "best possible" model given a specified set of contextual factors (in the sense of minimizing prediction error):

$$Model\ Completeness = \frac{\mathcal{E}_{base} - \mathcal{E}_{model}}{\mathcal{E}_{base} - \mathcal{E}_{irreducible}},$$

where $\mathcal{E}_{base}$ is the prediction error (in out-of-sample data) of the base model, which is the unconditional mean in our setting; $\mathcal{E}_{model}$ is the prediction error of the linear prediction model with the observed contextual factors; $\mathcal{E}_{irreducible}$ is the irreducible error associated with the observed contextual factors. Model completeness ranges from 0 to 1, with a lower value of model completeness indicating that incorporating nonlinearities could lead to greater decreases in prediction error (i.e., increases in predictive accuracy).[14]

FKLM suggest that $\mathcal{E}_{irreducible}$ can be measured using machine-learning methods such as decision trees because of their ability to capture a wide range of nonlinearities in the data. Hence, we use the random-forest algorithm, a method that combines multiple decision trees in a way that

[13] Irreducible error is measured for *a given set of contextual factors*. Including additional contextual factors in the prediction model can lower irreducible error, as we demonstrate in Section 5.2.
[14] FKLM use model completeness to measure the fraction of the prediction error that is due to "regularities in the data that the model does not capture." Given our setting of the linear model, we use slightly different terminology with the term "nonlinearities" instead of "regularities."

reduces overfitting, to capture $\mathcal{E}_{irreducible}$.[15] Specifically, $\mathcal{E}_{irreducible}$ is the prediction error from applying the random-forest algorithm with the four observed contextual factors (*life cycle*, *nature of investments*, *operational complexity*, and *information environment*) to predict governance choices. Similar to our earlier analysis, we measure prediction error using MSE and $\overline{\text{AUC}}$.

Table 4 Panel A reports our estimates of model completeness for antitakeover provisions when prediction error is measured using MSE. We find that completeness is 0.38 for staggered boards. The interpretation for this value is that the linear model can predict only 38% of the variation in staggered boards that can be predicted by the best possible model with the observed contextual factors. In other words, 62% of the *predictable variation*—the variation in staggered boards that can possibly be predicted given the observed contextual factors—is due to the nonlinear effects of the observed contextual factors on the usage of staggered boards. This is striking and suggests that nonlinearities are very important for understanding how context affects governance choices.

The importance of nonlinearities holds across other antitakeover provisions as well. The average completeness across all antitakeover provisions is 0.14, indicating that the linear model can predict only 14% of the predictable variation in antitakeover provisions, with the remaining 86% of the predictable variation attributed to nonlinearities.

Table 4 Panel B reports our estimates of model completeness when prediction error is measured using $\overline{\text{AUC}}$. The estimates of completeness tend to be higher in this case because the binary nature of governance choices heavily penalizes linear functional forms when prediction error is measured using MSE. However, our inferences remain the same. The average completeness across all antitakeover provisions is 0.39, indicating that the linear model can predict

[15] For details on the random-forest algorithm, see Biau and Scornet (2016).

only 39% of the predictable variation in antitakeover provisions, with the remaining 61% of the predictable variation captured by nonlinearities.

Table 5 reports estimates of model completeness for board characteristics. The average completeness across all board characteristics is 0.28 and 0.47 when prediction error is measured using MSE and $\overline{\text{AUC}}$, respectively. Similar to the case with antitakeover provisions, there is significant predictable variation in board characteristics that is due to the nonlinear effects of the observed contextual factors on board characteristics. The board characteristics with the highest completeness is *High Board Size* with a value of over 0.70, suggesting that across all board characteristics, the linear model is most suitable for understanding firms' choice of board size.

Overall, Tables 4 and 5 provide evidence that incorporating nonlinearities significantly improves the predictive accuracy of context for governance choices. Averaged across all governance mechanisms and both measures of prediction error (i.e., MSE and $\overline{\text{AUC}}$), the linear prediction model's completeness is 0.32. This suggests that exploring the nonlinear effects of the observed contextual factors on governance choices could be a fruitful way to improve our understanding for why firms choose the governance structures that they do.

5.2. Unobserved Context

Beyond incorporating nonlinearities, the linear model with observed contextual factors could also be potentially improved by including unobserved context (e.g., the CEO's preferences). While prior empirical studies commonly account for unobserved context through the use of firm fixed effects, this approach is not feasible in our prediction setting because there are firms in the out-of-sample data that do not belong in the training sample. To overcome this challenge, we propose a method to obtain information about unobserved context by applying the k-modes clustering algorithm over a firm's governance mechanisms (which are all binary variables).[16] Conceptually, k-modes clustering is an unsupervised machine-learning method that searches for patterns underlying firms' governance choices *without using any information from the observed contextual factors* in our linear prediction model. The algorithm outputs these patterns in the form of "clusters," which provide additional information about unobserved context that can potentially enhance the prediction model.

As an illustration, let $G = \{G_1, \ldots, G_n\}$ denote the set of binary governance mechanisms. Suppose we decide to form three clusters (we discuss how to choose the number of clusters below). The k-modes clustering is a function $\kappa(G)$ that maps the governance mechanisms into the set of clusters $C = \{C_1, C_2, C_3\}$ for each observation i. We then summarize these clusters into a single variable, *Unobserved Context*, where

$$Unobserved\ Context_i = \begin{cases} 1 & if\ C_i = C_1 \\ 2 & if\ C_i = C_2 \\ 3 & if\ C_i = C_3 \end{cases}$$

for each observation i. Note that an observation can only belong to one cluster at a time and that firms can change clusters over time.

We call the variable above "unobserved context" because the clusters that are outputted from the k-modes clustering algorithm do not use any information from the observed contextual factors. However, we recognize that the measure of unobserved context obtained from the k-modes clustering algorithm is unlikely to capture all types of unobserved context. As a result, our findings

[16] K-modes clustering is an extension of the k-means clustering algorithm but for clustering categorical data. That is, instead of computing means of clusters, the k-modes algorithm uses modes—the most frequent categories in a cluster—to determine cluster centers. For details on the k-modes clustering algorithm, see Chaturvedi et al. (2001).

provide a *lower bound* of the potential improvement from incorporating information about unobserved context.[17]

The key hyperparameter for the k-modes clustering algorithm is the number of clusters. To determine the optimal number of clusters, we use two statistics: the Silhouette Coefficient and the Calinski-Harabasz Index. They are both metrics to evaluate the quality of clusters. Intuitively, higher-quality clusters are those in which observations within a cluster are more similar and observations in different clusters are less similar. The Silhouette Coefficient measures how similar an observation is to its own cluster compared to another cluster and ranges from -1 (bad) to 1 (good). The Calinski-Harabasz Index measures the ratio of between-cluster variance to within-cluster variance, where higher values of the index suggest better clustering. Table 6 Panel A reports the values for these two statistics to determine the optimal number of clusters in the k-modes clustering algorithm. We estimate these statistics for clusters ranging between three and seven. The number of clusters that results in the highest Silhouette Coefficient and Calinski-Harabasz Index is three, and we therefore choose three clusters as the key hyperparameter in the k-modes clustering algorithm.

Having constructed the variable *Unobserved Context*, we next determine the potential improvement from including information about unobserved context in the prediction model. Specifically, we compare the irreducible error when both observed and unobserved contextual factors are used for prediction, $\varepsilon_{irreducible}(Obs\ and\ Unobs)$, to the irreducible error when only observed context is used, $\varepsilon_{irreducible}(Obs)$, which was determined in Section 5.1. The intuition for this comparison is that $\varepsilon_{irreducible}(Obs)$ is the prediction error from the "best possible" prediction

[17] Note again that our notion of "unobserved context" is relative to the observed contextual factors in our prediction model. While there could be additional relevant observable contextual features outside of our model, clear guidance on what they are is lacking from the existing theoretical and empirical literature.

we can make with only the observed contextual factors, while $\varepsilon_{irreducible}(Obs\ and\ Unobs)$ is the prediction error from the "best possible" prediction we can make using information from both observed and unobserved context. We are interested in the improvement in predictive accuracy, if any, from including information about unobserved context.

Table 6 Panel B compares the model with observed and unobserved context to the model with only observed context when measuring prediction error using MSE. Averaged across all antitakeover provisions, $\varepsilon_{irreducible}(Obs)$ is 0.12, as shown previously in Section 5.1, while $\varepsilon_{irreducible}(Obs\ and\ Unobs)$ is 0.09, a decrease in prediction error of 25%. Averaged across all board characteristics, $\varepsilon_{irreducible}(Obs)$ is 0.19, from Section 5.1, while $\varepsilon_{irreducible}(Obs\ and\ Unobs)$ is 0.15, a decrease in prediction error of 21%. Table 6 Panel C compares $\varepsilon_{irreducible}(Obs)$ and $\varepsilon_{irreducible}(Obs\ and\ Unobs)$ when measuring prediction error using $\overline{\text{AUC}}$. Averaged across all antitakeover provisions, prediction error decreases by 31% from including *Unobserved Context*. Averaged across all board characteristics, prediction error decreases by 34% from including *Unobserved Context*.

Averaged across all governance mechanisms and both measures of prediction error (i.e., MSE and $\overline{\text{AUC}}$), including unobserved context improves on the prediction model with observed context and nonlinearities, decreasing prediction error (i.e., increasing predictive accuracy) by 27%. Overall, Table 6 provides evidence that the use of unsupervised machine-learning algorithms like clustering can aid in the construction of additional contextual factors that may be more difficult to observe and yet are relevant for predicting governance choices.

6. Context Consistent Governance

6.1. Measure Construction

A major challenge in corporate governance research is measuring governance quality. Many prior studies measure governance quality through indices, which involve the linear aggregation of distinct governance mechanisms that are categorized as being unconditionally strong or weak (see Table 1). Other studies use simpler and possibly more interpretable measures, such as the proportion of independent directors or the stock ownership of independent directors. However, with little exception, prior studies do not attempt to account for contextual information in the measurement of governance quality. In this section, we construct a new measure of governance, *context consistent governance* (*CCG*), capturing how close a firm's actual governance structure is to the one predicted by its observed contextual factors.

It is not immediately clear that incorporating contextual information will improve measurement. For instance, suppose that one uses a linear model to predict the presence of governance mechanisms as a function of the observed contextual factors and then compares a firm's actual governance structure to the predicted one. In this case, even if a firm's governance structure deviates from the predicted one, the deviation may not imply low governance quality because there may be uncaptured nonlinearities. To overcome this challenge and construct a measure of context-specific governance with greater ability to distinguish between low- and high-quality governance, we use the prediction model developed in Section 5 that minimizes prediction error for the set of observed contextual factors. Specifically, this model predicts governance choices using the random-forest algorithm with the four observed contextual factors (*life cycle*, *nature of investments*, *operational complexity*, and *information environment*) incorporating potential nonlinearities.

Let G be the set of governance mechanisms: {*Staggered Board*, *Poison Pill*, *Unequal Voting Rights*, *Limits to Amend Bylaws*, *Limits to Amend Charter*, *Limits to Approve Mergers*, *High Board*

Size, *Low Board Independence*, *High Board Cooption*, and *CEO Duality*$\}$, and let g be an arbitrary element of G. Then, *CCG* is defined for firm i as:

$$CCG_i = -\sum_{g_i \in G_i} (g_i - \hat{g}_i)^2,$$

where $\hat{g}_i$ is the predicted likelihood of g_i for firm i using the prediction model described above. A higher value of *CCG* indicates that a firm's actual governance structure is closer to the one predicted by its contextual factors, with the highest possible value being zero. Table 7 Panel A plots the distribution of *CCG* in the out-of-sample data. *CCG* has a mean of -1.48 and a standard deviation of 0.62.

To evaluate our measure of context consistent governance, we follow prior studies and examine *CCG*'s associations with one-year ahead firm value and operating performance. As in our previous analyses, we evaluate the associations using the testing dataset (2,703 observations). We measure firm value as the market value of assets scaled by the book value of assets in year *t+1*. The market value of assets is the book value of assets plus the market value of common stock less the sum of the book value of common stock. We measure operating performance as operating income before depreciation scaled by total assets in year *t+1*. To benchmark the performance of *CCG*, we construct two unconditional governance indices using the same governance provisions as in *CCG*:

$$\begin{aligned} Antitakeover\ Index = {} & Staggered\ Board + Poison\ Pill + Unequal\ Voting\ Rights + Limits\ to\ Amend\ Bylaws + \\ & + Limits\ to\ Amend\ Charter + Limits\ to\ Approve\ Mergers. \end{aligned}$$

$$Entrenched\ Board\ Index = High\ Board\ Size + Low\ Board\ Independence + High\ Board\ Cooption + CEO\ Duality.$$

Antitakeover Index is the equal-weighted sum of the antitakeover provisions, while *Entrenched Board Index* is the equal-weighted sum of the board characteristics. We analyzed these antitakeover provisions and board characteristics in Sections 4 and 5.

6.2. Results

Table 7 Panel B reports *CCG*'s univariate out-of-sample associations with firm value and operating performance. All independent variables are standardized for ease of interpretation. Column (1) shows a positive and statistically significant association between *CCG* and *Firm* $Value_{t+1}$, consistent with *CCG* capturing high-quality governance. In terms of economic magnitude, a one standard deviation change in *CCG* is associated with a 0.16 change in *Firm* $Value_{t+1}$ (12% of its standard deviation). Column (2) shows that *Antitakeover Index* and *Entrenched Board Index* both have negative and statistically significant associations with firm value, consistent with prior studies that find these unconditional governance indices, which reflect greater management insulation from removal and lower board monitoring, are associated with lower firm value (e.g., Gompers et al., 2003; Bebchuk et al., 2009). Column (3) includes *CCG* together with *Antitakeover Index* and *Entrenched Board Index* and shows that *CCG* continues to have a positive and statistically significant association with firm value, suggesting context consistent governance is not captured by unconditional governance indices. Columns (4-6) show that *CCG* also has a positive and statistically significant association with *Operating* $Performance_{t+1}$ that is not subsumed by unconditional governance indices. In terms of economic magnitude, Column (4) shows that a one standard deviation change in *CCG* is associated with a 0.005 change in *Firm* $Value_{t+1}$ (6% of its standard deviation).

Table 7 Panel C reports *CCG*'s multivariate out-of-sample associations with firm value and operating performance. Here, we control for all observed contextual proxies. Columns (1-3) show that *CCG* has a positive and statistically significant association with *Firm Value*$_{t+1}$, while Columns (4-6) show that *CCG* has a positive and statistically significant association with *Operating Performance*$_{t+1}$, indicating that the positive associations remain after controlling for the direct associations between the observed contextual proxies and the firm outcomes.

A natural question is whether *CCG* is a stronger indicator of governance quality than unconditional governance indices. Based on the findings in Table 7 Panels B and C, the answer would appear to be in the affirmative. In Table 7 Panel C, Column (1) shows that a one standard deviation change in *CCG* is associated with a 0.13 change in *Firm Value*$_{t+1}$, while Column (2) shows that a one standard deviation change in *Antitakeover Index* is associated with only a 0.04 change in *Firm Value*$_{t+1}$. Column (4) shows that a one standard deviation change in *CCG* is associated with a 0.006 change in *Operating Performance*$_{t+1}$, while Column (5) shows that a one standard deviation change in *Antitakeover Index* is associated with a smaller 0.004 change in *Operating Performance*$_{t+1}$. Overall, our results suggest that *CCG* captures high-quality governance and is a stronger indicator of governance quality than unconditional governance indices. More broadly, they highlight the value of integrating context into the measurement of corporate governance.

7. Conclusion

This paper develops a novel prediction approach to investigate how context shapes firms' governance choices. We find that observed contextual factors, especially a firm's life cycle and operational complexity, have substantial predictive power for out-of-sample governance choices.

This finding provides new evidence in support of the view that governance is inherently context dependent. Furthermore, using the framework in Fudenberg et al. (2022), we assess the completeness of the linear model, which has been the workhorse model in the empirical literature to examine the relations between firm characteristics and governance mechanisms. We show that the linear model is highly incomplete and could be substantially improved by incorporating the nonlinear effects of context on governance choices. We also propose a method to obtain information about unobserved context and show that utilizing the information further improves predictive accuracy.

Leveraging insights from the prediction analysis, we propose a new measure of governance quality, context consistent governance (CCG), which captures how close a firm's actual governance structure is to the one predicted by its contextual factors. We show that context consistent governance exhibits stronger associations with future firm value and operating performance compared to unconditional governance indices. Altogether, our prediction approach offers new insights into the economics and measurement of corporate governance, and suggests a framework for future research that uses prediction methods and machine-learning algorithms to complement other techniques.

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Table 1: Common Proxies for Corporate Governance. This table reports summary statistics for how corporate governance is measured in the academic literature. We search accounting and finance journals (JAE, JAR, TAR, JFE, JF, and RFS) over the five-year period 2016-2020 and identify all papers that employ some measure of governance quality in their empirical analyses. The total number of such papers is 210. The G-Index was first constructed in Gompers et al. (2003), while the E-Index was first constructed in Bebchuk et al. (2009). The percentages add up to more than 100% in Panel C because some papers use multiple governance measures.

Panel A: Distribution of Papers Across Journals Between 2016 and 2020.

	Number of Papers	Percentage of All Papers
JAE Journal of Accounting and Economics	34	16%
JAR Journal of Accounting Research	12	6%
TAR The Accounting Review	50	24%
JF Journal of Finance	11	5%
JFE Journal of Financial Economics	58	28%
RFS Review of Financial Studies	45	21%
Total	210	100%

Panel B: Governance Indices.

	Number of Papers	Percentage of All Papers
Any governance index	120	57%
G-Index	50	24%
E-Index	45	21%

Panel C: Other Common Measures.

	Number of Papers	Percentage of All Papers
Board Independence	92	44%
Board Size	63	30%
CEO Duality	56	27%
CEO Tenure	17	8%
Insider/CEO Ownership	17	8%
Staggered Board	12	6%
Board Ownership	11	5%
# Board Meetings	7	3%
Poison Pill	6	3%
Dual Class Structure	4	2%
Audit Committee Size	3	1%

Table 2: Descriptive Statistics. This table reports descriptive statistics for our sample in three panels. The sample consists of 13,711 firm-year observations covering the years 2007 through 2021. There are 1,700 unique firms. All variables are defined in Appendix A.

Panel A: Summary Statistics. Antitakeover provisions and board characteristics are binary indicator variables. *Antitakeover Index* is the sum of antitakeover provisions and *Entrenched Board Index* is the sum of board characteristics.

	N	Mean	SD	P25	P50	P75
Antitakeover Provisions						
Staggered Board	13,711	0.41	0.49	0.00	0.00	1.00
Poison Pill	13,711	0.12	0.32	0.00	0.00	0.00
Unequal Voting Rights	13,711	0.06	0.23	0.00	0.00	0.00
Limits to Amend Bylaws	13,711	0.38	0.49	0.00	0.00	1.00
Limits to Amend Charter	13,711	0.51	0.50	0.00	1.00	1.00
Limits to Approve Mergers	13,711	0.23	0.42	0.00	0.00	0.00
Antitakeover Index	13,711	1.71	1.40	0.00	2.00	3.00
Board Characteristics						
High Board Size	13,711	0.47	0.50	0.00	0.00	1.00
Low Board Independence	13,711	0.54	0.50	0.00	1.00	1.00
High Board Cooption	13,711	0.50	0.50	0.00	0.00	1.00
CEO Duality	13,711	0.57	0.50	0.00	1.00	1.00
Entrenched Board Index	13,711	2.08	1.05	1.00	2.00	3.00
Contextual Factors						
Life Cycle						
Firm Age	13,711	2.55	0.42	2.30	2.64	2.89
Operational Maturity	13,711	0.64	0.48	0.00	1.00	1.00
Nature of Investments						
R&D Investment	13,711	0.02	0.04	0.00	0.00	0.02
Relationship Investment	13,711	0.29	0.27	0.00	0.26	0.49
Operational Complexity						
Firm Size	13,711	8.35	1.68	7.10	8.21	9.47
Leverage	13,711	0.24	0.18	0.08	0.22	0.36
Number of Segments	13,711	3.08	1.91	1.00	3.00	4.00
Information Environment						
Number of Analysts	13,711	3.91	0.81	3.33	3.95	4.52
Analyst Forecast Dispersion	13,711	0.01	0.03	0.00	0.00	0.01
Analyst Forecast Error	13,711	0.01	0.04	0.00	0.00	0.01
Firm Outcomes						
Firm Value$_{t+1}$	13,711	1.99	1.31	1.15	1.54	2.30
Operating Performance$_{t+1}$	13,711	0.12	0.08	0.07	0.12	0.17

Panel B: Correlations Across Governance Mechanisms.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Staggered Board	1.00									
(2) Poison Pill	0.15***	1.00								
(3) Unequal Voting Rights	-0.03***	-0.05***	1.00							
(4) Limits to Amend Bylaws	0.35***	0.07***	-0.09***	1.00						
(5) Limits to Amend Charter	0.37***	0.08***	-0.07***	0.58***	1.00					
(6) Limits to Approve Mergers	0.14***	0.08***	-0.01	0.09***	0.29***	1.00				
(7) High Board Size	-0.14***	-0.06***	-0.00	-0.06***	-0.00	0.10***	1.00			
(8) Low Board Independence	0.10***	0.03***	0.16***	0.04***	0.02	0.04***	-0.04***	1.00		
(9) High Board Cooption	0.01	-0.01	0.03***	0.01	0.01	-0.03***	-0.07***	-0.01	1.00	
(10) CEO Duality	0.03***	0.03**	0.11***	-0.02*	-0.03***	0.08***	0.09***	0.09***	0.16***	1.00

Panel C: Correlations Across Contextual Variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Firm Age	1.00									
(2) Operational Maturity	0.06***	1.00								
(3) R&D Investment	-0.01	0.04***	1.00							
(4) Relationship Investment	0.01	0.07***	0.29***	1.00						
(5) Firm Size	0.22***	-0.07***	-0.25***	-0.18***	1.00					
(6) Leverage	0.07***	-0.06***	-0.20***	0.02*	0.21***	1.00				
(7) Number of Segments	0.11***	0.03***	-0.18***	-0.09***	0.32***	0.14***	1.00			
(8) Number of Analysts	0.06***	0.02**	-0.04***	-0.07***	0.58***	0.13***	0.06***	1.00		
(9) Analyst Forecast Dispersion	-0.06***	-0.06***	-0.02	-0.02	-0.03**	0.11***	-0.01	0.03***	1.00	
(10) Analyst Forecast Error	-0.08***	-0.06***	-0.02**	-0.02**	-0.03***	0.09***	-0.00	0.00	0.92***	1.00

Table 3: Observed Context and Governance Choices. This table reports the results of predicting governance choices in out-of-sample data (2,703 observations), based on observed contextual factors and our linear prediction model. We measure prediction error using MSE and $\overline{\text{AUC}}$ (defined in the Section 4.1). *No Context* is a base model that does not incorporate any observed contextual factors (i.e., it is the unconditional mean). *Life Cycle* includes *Firm Age* and *Operational Maturity* as contextual variables in the prediction model. *Nature of Investments* includes *R&D Investment* and *Relationship Investment* as contextual variables. *Operational Complexity* includes *Firm Size*, *Leverage*, and *Number of Segments* as contextual variables. *Information Environment* includes *Number of Analysts*, *Analyst Forecast Dispersion*, and *Analyst Forecast Error* contextual variables. *All Context* includes all observed contextual factors in the prediction model. With t-statistics, we compare the MSE in the column to the MSE under the base model (*No Context*). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Note that we cannot compute t-statistics when measuring prediction error using $\overline{\text{AUC}}$ because $\overline{\text{AUC}}$ is a single summary measure for a model's ability to distinguish between classes. All variables are defined in Appendix A.

Panel A: Prediction Error is Measured Using MSE.

	No Context	Life Cycle	Nature of Investments	Operational Complexity	Information Environment	All Context
Staggered Board	0.244	0.230***	0.241	0.219***	0.233***	0.212***
Poison Pill	0.106	0.105	0.106	0.104	0.106	0.103
Unequal Voting Rights	0.044	0.044	0.044	0.044	0.044	0.044
Limits to Amend Bylaws	0.236	0.231	0.235	0.231	0.234	0.227***
Limits to Amend Charter	0.250	0.248	0.250	0.246***	0.246***	0.243***
Limits to Approve Mergers	0.168	0.168	0.165	0.166	0.167	0.163
High Board Size	0.249	0.242***	0.238***	0.171***	0.232***	0.169***
Low Board Independence	0.249	0.246*	0.249	0.240***	0.248	0.238***
High Board Cooption	0.250	0.248**	0.250	0.249	0.250	0.248*
CEO Duality	0.247	0.246	0.245	0.243*	0.244	0.239***
Average Across Governance Choices	0.204	0.201	0.202	0.191	0.200	0.188
N	2,703	2,703	2,703	2,703	2,703	2,703

Panel B: Prediction Error is Measured Using $\overline{\text{AUC}}$.

	No Context	Life Cycle	Nature of Investments	Operational Complexity	Information Environment	All Context
Staggered Board	0.500	0.357	0.437	0.312	0.369	0.281
Poison Pill	0.500	0.300	0.430	0.374	0.444	0.288
Unequal Voting Rights	0.500	0.465	0.403	0.508	0.546	0.422
Limits to Amend Bylaws	0.500	0.416	0.468	0.415	0.450	0.384
Limits to Amend Charter	0.500	0.449	0.476	0.428	0.419	0.402
Limits to Approve Mergers	0.500	0.477	0.423	0.432	0.442	0.380
High Board Size	0.500	0.410	0.396	0.174	0.346	0.171
Low Board Independence	0.500	0.433	0.482	0.395	0.467	0.380
High Board Cooption	0.500	0.453	0.492	0.468	0.501	0.448
CEO Duality	0.500	0.459	0.461	0.423	0.432	0.395
Average Across Governance Choices	0.500	0.422	0.447	0.393	0.442	0.355
N	2,703	2,703	2,703	2,703	2,703	2,703

Table 4: Model Completeness – Antitakeover Provisions. This table quantifies the performance of the linear prediction model for antitakeover provisions using the measure of model completeness introduced in Fudenberg et al. (2022):

$$Model\ Completeness = \frac{\mathcal{E}_{base} - \mathcal{E}_{model}}{\mathcal{E}_{base} - \mathcal{E}_{irreducible}}.$$

$\mathcal{E}_{base}$ is the prediction error (in out-of-sample data) of the base model, which is the unconditional mean in our setting. $\mathcal{E}_{model}$ is the prediction error of the linear prediction model with observed contextual factors (see Table 3). $\mathcal{E}_{complete}$ is the irreducible error, which we estimate following Fudenberg et al. (2022) using the prediction error of a machine-learning model with observed contextual factors. We use the random-forest algorithm as our machine-learning model. Model completeness ranges from 0 to 1, with a higher value of model completeness indicating that the linear prediction model performs better. We measure prediction error using MSE and $\overline{\text{AUC}}$.

Panel A: Prediction Error is Measured Using MSE.

	Staggered Board	**Poison Pill**	**Unequal Voting Rights**	**Limits to Amend Bylaws**	**Limits to Amend Charter**	**Limits to Approve Mergers**	**Average Across All Provisions**
$\mathcal{E}_{base}$	0.244	0.106	0.044	0.236	0.250	0.168	0.175
$\mathcal{E}_{model}$	0.212	0.103	0.044	0.227	0.243	0.163	0.165
$\mathcal{E}_{irreducible}$	0.159	0.082	0.034	0.173	0.175	0.116	0.123
$\mathcal{E}_{base} - \mathcal{E}_{model}$	0.032	0.003	0.000	0.009	0.007	0.005	0.009
$\mathcal{E}_{base} - \mathcal{E}_{irreducible}$	0.085	0.024	0.010	0.063	0.075	0.051	0.051
Model Completeness	0.377	0.139	0.011	0.145	0.095	0.090	0.143

Panel B: Prediction Error is Measured Using $\overline{\text{AUC}}$.

	Staggered Board	**Poison Pill**	**Unequal Voting Rights**	**Limits to Amend Bylaws**	**Limits to Amend Charter**	**Limits to Approve Mergers**	**Average Across All Provisions**
$\mathcal{E}_{base}$	0.500	0.500	0.500	0.500	0.500	0.500	0.500
$\mathcal{E}_{model}$	0.281	0.288	0.422	0.384	0.402	0.380	0.359
$\mathcal{E}_{irreducible}$	0.141	0.140	0.113	0.174	0.153	0.124	0.141
$\mathcal{E}_{base} - \mathcal{E}_{model}$	0.219	0.212	0.078	0.116	0.098	0.120	0.141
$\mathcal{E}_{base} - \mathcal{E}_{irreducible}$	0.359	0.360	0.387	0.326	0.347	0.376	0.359
Model Completeness	0.611	0.588	0.202	0.357	0.284	0.319	0.393

Table 5: Model Completeness – Board Characteristics. This table quantifies the performance of the linear prediction model for board characteristics using the measure of model completeness introduced in Fudenberg et al. (2022):

$$Model\ Completeness = \frac{\mathcal{E}_{base} - \mathcal{E}_{model}}{\mathcal{E}_{base} - \mathcal{E}_{complete}}.$$

$\mathcal{E}_{base}$ is the prediction error (in out-of-sample data) of the base model, which is the unconditional mean in our setting. $\mathcal{E}_{model}$ is the prediction error of the linear prediction model with observed contextual factors (see Table 3). $\mathcal{E}_{complete}$ is the irreducible error, which we estimate following Fudenberg et al. (2022) using the prediction error of a machine-learning model with observed contextual factors. We use the random-forest algorithm as our machine-learning model. Model completeness ranges from 0 to 1, with a higher value of model completeness indicating that the linear prediction model performs better. We measure prediction error using MSE and $\overline{\text{AUC}}$.

Panel A: Prediction Error is Measured Using MSE.

	High Board Size	**Low Board Independence**	**High Board Cooption**	**CEO Duality**	**Average Across All Board Characteristics**
$\mathcal{E}_{base}$	0.249	0.249	0.250	0.247	0.249
$\mathcal{E}_{model}$	0.169	0.238	0.248	0.239	0.223
$\mathcal{E}_{irreducible}$	0.137	0.192	0.216	0.195	0.185
$\mathcal{E}_{base} - \mathcal{E}_{model}$	0.080	0.011	0.002	0.008	0.025
$\mathcal{E}_{base} - \mathcal{E}_{irreducible}$	0.113	0.057	0.034	0.052	0.064
Model Completeness	0.711	0.190	0.060	0.156	0.279

Panel B: Prediction Error is Measured Using $\overline{\text{AUC}}$.

	High Board Size	**Low Board Independence**	**High Board Cooption**	**CEO Duality**	**Average Across All Board Characteristics**
$\mathcal{E}_{base}$	0.500	0.500	0.500	0.500	0.500
$\mathcal{E}_{model}$	0.171	0.380	0.448	0.395	0.349
$\mathcal{E}_{irreducible}$	0.112	0.215	0.283	0.224	0.208
$\mathcal{E}_{base} - \mathcal{E}_{model}$	0.329	0.120	0.052	0.105	0.151
$\mathcal{E}_{base} - \mathcal{E}_{irreducible}$	0.388	0.285	0.217	0.276	0.292
Model Completeness	0.848	0.419	0.240	0.379	0.471

Table 6: Unobserved Context and Governance Choices. This table quantifies the importance of unobserved context by comparing the irreducible error when both observed and unobserved context are used for prediction to the irreducible error when only observed context is used. We measure unobserved context using the k-modes clustering algorithm (see Section 5 for details). $\mathcal{E}_{irreducible}(Obs\ \&\ Unobs)$ is the irreducible error when both observed and unobserved context are both used for prediction, and we estimate it using the prediction error of a machine-learning model with observed and unobserved contextual factors. $\mathcal{E}_{irreducible}(Obs)$ is the irreducible error when only observed context is used for prediction, and we estimate it using the prediction error of a machine-learning model with observed contextual factors. We use the random-forest algorithm as our machine-learning model. Panel A reports the values for two statistics used to determine the optimal number of clusters: the Silhouette Coefficient and the Calinski-Harabasz Index. Panels B and C present the results on irreducible error. We measure prediction error using MSE and $\overline{\text{AUC}}$.

Panel A: Determining the Number of Clusters.

Number of Clusters	Silhouette Coefficient	Calinski-Harabasz Index
3	0.247	1871.439
4	0.201	1607.411
5	0.199	1420.355
6	0.181	1255.432
7	0.163	1161.253

Panel B: Prediction Error is Measured Using MSE.

	Staggered Board	Poison Pill	Unequal Voting Rights	Limits to Amend Bylaws	Limits to Amend Charter	Limits to Approve Mergers	Average Across All Provisions
$\mathcal{E}_{irreducible}(Obs)$	0.159	0.082	0.034	0.173	0.175	0.116	0.123
$\mathcal{E}_{irreducible}(Obs\ \&\ Unobs)$	0.106	0.080	0.033	0.108	0.112	0.113	0.092

	High Board Size	Low Board Independence	High Board Cooption	CEO Duality	Average Across All Board Characteristics
$\mathcal{E}_{irreducible}(Obs)$	0.137	0.192	0.216	0.195	0.185
$\mathcal{E}_{irreducible}(Obs\ \&\ Unobs)$	0.124	0.166	0.166	0.155	0.153

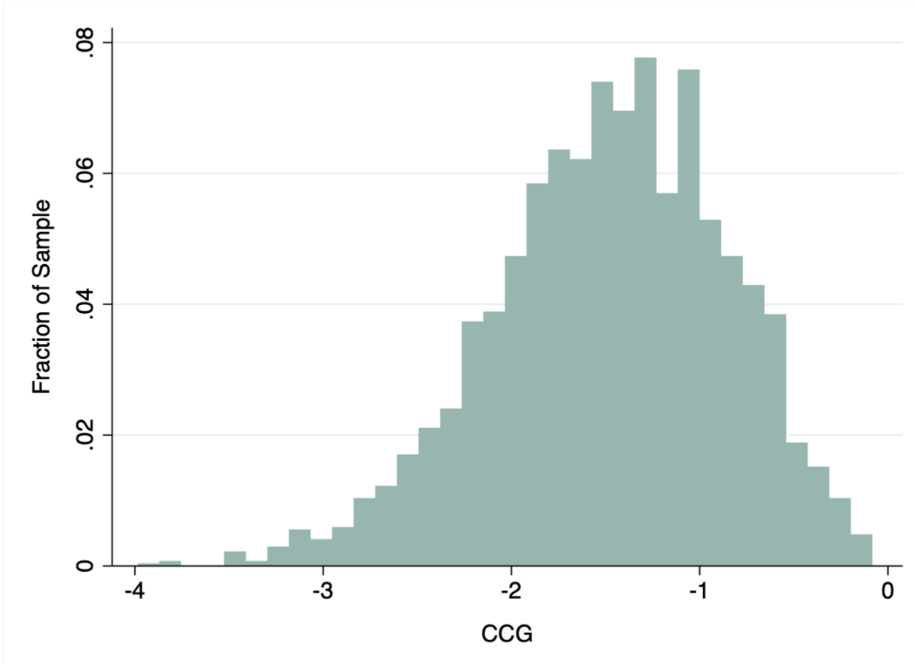
Panel C: Prediction Error is Measured Using $\overline{\text{AUC}}$.

	Staggered Board	Poison Pill	Unequal Voting Rights	Limits to Amend Bylaws	Limits to Amend Charter	Limits to Approve Mergers	Average Across All Provisions
$\mathcal{E}_{irreducible}(Obs)$	0.141	0.140	0.113	0.174	0.153	0.124	0.141
$\mathcal{E}_{irreducible}(Obs\ \&\ Unobs)$	0.072	0.131	0.097	0.081	0.073	0.126	0.097

	High Board Size	Low Board Independence	High Board Cooption	CEO Duality	Average Across All Board Characteristics
$\mathcal{E}_{irreducible}(Obs)$	0.112	0.215	0.283	0.224	0.208
$\mathcal{E}_{irreducible}(Obs\ \&\ Unobs)$	0.093	0.157	0.160	0.142	0.138

Table 7: Context Consistent Governance (*CCG*). This table reports our results on context consistent governance (*CCG*). *CCG* captures how close a firm's actual governance structure is to the governance structure predicted by its observed contextual factors (see Section 6 for details). In Panels B and C, we examine *CCG*'s association with firm value and operating performance in out-of-sample data. All independent variables are standardized for ease of interpretation. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

Panel A: Distribution of *CCG*. This figure plots our measure of context consistent governance (*CCG*) in the out-of-sample data (2,703 observations). *CCG* has a mean of -1.48 and a standard deviation of 0.62. The highest possible value of *CCG* is zero. Higher values of *CCG* indicate that the firm's governance structure is closer to what is predicted by its observed contextual factors.



Panel B: Evaluating *CCG* – Univariate.

	Firm Value$_{t+1}$			Operating Performance$_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
CCG	0.162***		0.168***	0.00459***		0.00360**
	(6.60)		(6.36)	(2.83)		(2.06)
Antitakeover Index		-0.0604**	-0.000269		-0.00501***	-0.00372**
		(-2.44)	(-0.01)		(-3.08)	(-2.14)
Entrenched Board Index		-0.0544**	-0.0711***		-0.00344**	-0.00380**
		(-2.20)	(-2.88)		(-2.12)	(-2.33)
N	2,703	2,703	2,703	2,703	2,703	2,703
R^2	0.016	0.004	0.019	0.003	0.005	0.007

Panel C: Evaluating *CCG* – Multivariate.

	Firm Value$_{t+1}$			Operating Performance$_{t+1}$		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
CCG	0.125***		0.123***	0.00585***		0.00533***
	(5.64)		(5.25)	(4.11)		(3.55)
Antitakeover Index		-0.0408*	-0.00212		-0.00376***	-0.00208
		(-1.79)	(-0.09)		(-2.58)	(-1.36)
Entrenched Board Index		0.0359	0.0248		-0.00109	-0.00157
		(1.62)	(1.12)		(-0.77)	(-1.10)
Firm Age	0.0282	0.0227	0.0283	0.00742***	0.00703***	0.00727***
	(1.04)	(0.83)	(1.04)	(4.26)	(4.02)	(4.17)
Operational Maturity	0.0970***	0.107***	0.0979***	0.0140***	0.0143***	0.0139***
	(4.36)	(4.81)	(4.40)	(9.77)	(10.03)	(9.74)
R&D Investment	0.299***	0.321***	0.300***	-0.00977***	-0.00884***	-0.00973***
	(11.00)	(11.84)	(11.02)	(-5.61)	(-5.10)	(-5.57)
Relationship Investment	-0.0237	-0.0231	-0.0241	0.00311**	0.00311**	0.00307**
	(-0.97)	(-0.94)	(-0.99)	(1.99)	(1.99)	(1.96)
Firm Size	-0.319***	-0.299***	-0.325***	-0.0182***	-0.0171***	-0.0182***
	(-8.46)	(-7.86)	(-8.50)	(-7.52)	(-7.00)	(-7.41)
Leverage	0.0278	0.0257	0.0302	0.00591***	0.00554***	0.00573***
	(1.09)	(1.00)	(1.18)	(3.60)	(3.35)	(3.48)
Number of Segments	-0.0401	-0.0362	-0.0394	0.000865	0.001000	0.000859
	(-1.59)	(-1.43)	(-1.56)	(0.53)	(0.62)	(0.53)
Number of Analysts	0.312***	0.298***	0.311***	0.0149***	0.0143***	0.0148***
	(9.77)	(9.32)	(9.73)	(7.28)	(6.97)	(7.23)
Analyst Forecast Dispersion	-0.209***	-0.214***	-0.208***	-0.0202***	-0.0205***	-0.0202***
	(-4.26)	(-4.32)	(-4.23)	(-6.40)	(-6.47)	(-6.41)
Analyst Forecast Error	0.0281	0.0281	0.0280	-0.000555	-0.000623	-0.000624
	(0.58)	(0.58)	(0.58)	(-0.18)	(-0.20)	(-0.20)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,703	2,703	2,703	2,703	2,703	2,703
R^2	0.345	0.338	0.345	0.376	0.373	0.376

Appendix A. Variable Definitions

This appendix provides definitions for the key variables used in our analysis.

Staggered Board	An indicator variable equal to one if the firm has a board in which directors are divided into separate classes with each class being elected to overlapping terms.
Poison Pill	An indicator variable equal to one if the firm has a shareholder right that is triggered in the event of an unauthorized change in control that renders the target company financially unattractive or dilutes the voting power of the acquirer.
Unequal Voting Rights	An indicator variable equal to one if the firm has unequal voting rights across common shareholders.
Limits to Amend Bylaws	An indicator variable equal to one if the firm has a provision limiting shareholders' ability through majority vote to amend the corporate bylaws.
Limits to Amend Charter	An indicator variable equal to one if the firm has a provision limiting shareholders' ability through majority vote to amend the corporate charter.
Limits to Approve Mergers	An indicator variable equal to one if the firm has a provision limiting shareholders' ability through majority vote to approve a merger.
Antitakeover Index	The sum of *Staggered Board*, *Poison Pill*, *Unequal Voting Rights*, *Limits to Amend Bylaws*, *Limits to Amend Charter*, and *Limits to Approve Merger*.
CEO Duality	An indicator variable equal to one if the CEO is also chairman of the board.
High Board Size	An indicator variable equal to one if the number of directors that sit on the board is above the median.
Low Board Independence	An indicator variable equal to one if the proportion of independent non-executive directors on the board is below the median.
High Board Cooption	An indicator variable equal to one if the proportion of directors appointed after the CEO assumes office is above the median.
Entrenched Board Index	The sum of *High Board Size*, *Low Board Independence*, *High Board Cooption*, and *CEO Duality*.
Firm Age	The natural log of the number of years that the firm has been listed on Compustat.
Operational Maturity	An indicator variable equal to one if the firm is at a mature stage according to cash-flow patterns developed in Dickinson (2011).
R&D Investment	R&D expenditures scaled by total assets.
Relationship Investment	The fraction of total sales that are due to the firm's largest customer.
Firm Size	The natural log of total assets.
Leverage	Short-term plus long-term debt scaled by total assets.
Number of Segments	The number of business segments with positive sales.
Number of Analysts	The natural log of the number of analysts following the firm.
Analyst Forecast Dispersion	The standard deviation of the annual earnings per share forecasts.
Analyst Forecast Error	The absolute value of the difference between the actual and forecasted annual earnings per share.
Firm Value$_{t+1}$	The market value of assets scaled by the book value of assets in year $t+1$.
Operating Performance$_{t+1}$	Operating income before depreciation scaled by total assets in year $t+1$.