Appointing Audit Committee Directors

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ABSTRACT:

Prior literature focuses on the relationship between audit committee (AC) characteristics and financial reporting outcomes, yet little is known about the AC appointment process. Using a large dataset of tens of thousands of potential director candidates, we use machine learning to select a director based on which candidate is predicted to have the best performance based on a specific company's characteristics. We then identify characteristics of actual appointees that appear to be under- or overweighted when compared to machine-selected candidates with the highest predicted future performance. Across more than 30 AC member characteristics, we find that current selection processes overweight expected benefits from foreign operations experience, law degrees, network potential, and private board experience. In contrast, they tend to underweight potential benefits from CPA certification, gender diversity, operating experience, and technology experience. We demonstrate that appointments with greater deviations between the actual and machine-selected appointee have a higher likelihood of making material misstatements in future periods, suggesting that these potential biases have direct effects on the effectiveness of ACs in overseeing financial reporting. Deviations between the actual and machine-selected appointee are higher when there is a rush to fill the position or when the actual appointee shares previous connections with either the nominating committee or other board members. Our findings should be of interest to investors advocating for proxy access, to nominating committees tasked with identifying future board members, and to regulators examining the efficacy of the current nomination system.

Keywords: audit committees; corporate governance; director labor market; machine learning; shareholder voting; proxy advisors

JEL Classification: G34, M41

Data Availability: Data are available from the public sources cited in the text.

1. Introduction

Since the corporate accounting scandals of the early 2000s and the passage of the Sarbanes-Oxley Act of 2002 (SOX), audit committee (AC) composition has been of increasing interest to companies and policymakers, spurring the creation of a burgeoning academic literature. Most of this research examines the relationship between various AC characteristics and financial reporting outcomes (Klein 2002; Abbott et al. 2004; Agrawal and Chada 2005; Dhaliwal et al. 2010; Carcello et al. 2011a, 2011b; Krishnan et al. 2011; Bryan et al. 2013; Cohen et al. 2014; Chen et al. 2015; Lisic et al. 2016; Cassell et al. 2018). Little is known, however, about the efficacy of the AC appointment process and how characteristics of appointed AC members differ from other potential candidates. Because prior literature finds that CEOs and members of the board have significant influence in the AC appointment process, which may lead to suboptimal decisions,[1] we use objective models to predict the future performance for potential candidates of each open AC position and then we compare the characteristics of actual appointed candidates with those of the predicted best-performing candidates.

Identifying differences between actual appointees and machine-selected candidates helps us better understand potential biases in director appointments. Prior studies have empirically examined bias in director appointments to the board in general, and document that this bias results in the appointment of a largely homogenous group of older, male directors that lacks diversity (Westphal and Zajac 1995; Shivdasani and Yermack 1999; Westphal and Stern 2007;

[1] Beasley et al. (2009, 81), for example, find that audit committee members are often appointed because of "their previous contact with management or other directors" and because of their financial expertise. Cohen et al. (2013) and Clune et al. (2014) interview audit committee and nominating committee members, respectively, and report substantial CEO influence in the audit committee nomination and selection process. Archival evidence suggests that CEO influence over audit committee members is associated with poor financial reporting quality (e.g., Carcello et al. 2011b; Lisic et al. 2016; Cassell et al. 2018).

Zhu and Westphal 2014; Erel et al. 2018).[2] However, none of these studies specifically examine and focus on appointments to the AC, and only Erel et al. (2018) draw conclusions about potential biases as compared to a realistic pool of potential directors. Examining the AC appointment process on its own is important because the tasks assigned to an AC member (e.g., overseeing financial reporting quality and internal controls) differ substantially from general board membership tasks (e.g., overseeing firm strategy and profitability), and as such, the desired characteristics of an AC member may differ from those expected of general board membership. Drawing conclusions from the perspective of a realistic pool of potential (but unappointed) directors is important because it ensures that conclusions related to shortages in actual appointees (e.g., gender or age diversity) cannot be attributed to a lack of a particular characteristic in the company's potential director pool.

Importantly, our research method does not require any assumptions about which characteristics are or are not *theoretically* ideal for an AC member. Instead, we use historical appointees to train our models, currently practicing directors and executives to form our potential pool of candidates, and realistic assumptions about the maximum number of appointments per potential director to avoid "superstar" directors that logistically cannot be assigned to every company.

We conduct the data analysis in two phases. First, we use out-of-sample data from actual appointments to identify the determinants associated with higher AC director-specific "performance"; i.e., the characteristics that would ideally be preferred based on a specific company's characteristics. We do this by training algorithms in five-year rolling windows with

[2] Specifically, Westphal and Zajac (1995), Westphal and Stern (2007), and Zhu and Westphal (2014) all document a bias toward appointing directors who are demographically similar to the CEO. Since CEOs are disproportionately male and disproportionately older, this bias is one of the factors contributing to the lack of gender and age diversity on corporate boards.

actual AC appointees between 2003 and 2014 and their respective director-specific performance in the first three years of their directorships (i.e., director-specific performance in 2004–2006 for appointees in 2003; and director specific-performance in 2015–2017 for appointees in 2014). To identify the director and company characteristics to include in our models, we rely on prior literature that examines the association between specific director characteristics and financial reporting quality. We look at prior education and licensure (e.g., CPA, MBA, law degree), professional experience (e.g., industry accounting, public accounting, technology, foreign operations, etc.), previous officer positions held (e.g., CFO, COO, and CEO), competing demands on the director's time (e.g., concurrent director or officer positions), professional network size, association with previous frauds, and geographic distance between the board member and the company. The company characteristics we include are those that should impact the quality and level of oversight expertise needed. They include size, complexity, performance, institutional ownership, reputation, and the external auditor. Because AC directors act as a team, we also consider the composition of the AC immediately preceding the new appointment (i.e., average age, tenure, financial expertise, and gender of current AC members).

Second, after determining which specific measures of director performance and which specific algorithms provide the best predictive models, we then use a large sample of potential candidates' characteristics to identify the machine-selected appointee for actual AC seats between 2008 and 2015. Specifically, for each newly appointed AC director *j* at company *i* in year *t*, we use the respective five-year trailing out-of-sample model to predict future performance for every independent candidate in the potential director pool in year *t*. We then assign the candidate with the highest-predicted future performance (director *k*) as the machine-selected appointee for director *j*'s seat. Univariate differences between the actual appointee director *j* and the machine-selected appointee director k make it possible for us to determine which director characteristics are under-appointed (i.e., viewed with bias) in the director labor market and which director characteristics are over-appointed in that market (i.e., unjustly favored). A data flow diagram of our process is reported in Figure 1.

This methodology is based on three key assumptions that warrant further discussion. The first is that in order to identify machine-selected appointments, we need a fair measure of director-specific performance in order to determine which AC characteristics are predictive of future success given the company and AC characteristics at the time of appointment. The AC is primarily responsible for overseeing external audit, internal audit, and financial reporting quality (e.g., Carcello et al. 2011b). This suggests that financial reporting quality measures are an ideal measure of AC-specific performance. However, financial reporting quality is a firm-level measure that does not capture variation in individual performance within committees. Instead, we use shareholder voting outcomes and Institutional Shareholder Services (ISS) proxy advisor voting recommendations to measure director performance because they are specific to the director. The recommendation criteria used by ISS are based on consideration of both company-specific financial reporting failures and director-specific characteristics (Kachelmeier et al. 2016), suggesting that they are an effective proxy for AC director-specific performance.[3] Because directors are expected to experience a learning curve with immediate appointment (Russell Reynolds Associates 2018) and because companies can have staggered voting periods

[3] We recognize that the voting and nomination process itself is not without its own potential forms of bias (Larcker et al. 2015; Hayne and Vance 2019; Malenko and Malenko 2019), but this allows us to measure performance from the perspective of the shareholders responsible for ultimately having a say in director performance. Further, we are not aware of any other director-specific measures of performance other than compensation and meeting attendance, which are largely fixed relative to firm-specific policies and unlikely to capture cross-sectional variation in the quality of each director's performance.

(e.g., specific directors may only be voted on once every three years), we measure performance using the first three years of a director's appointment to the AC.

Our second key assumption is that we can reasonably identify the pool of potential board candidates. We use the population of more than 75,000 active executives and board members in BoardEx, which includes directors serving both private and public companies, to identify suitable candidates ("potential candidates"). For each open board seat, we eliminate any potential candidates who would violate independence requirements (e.g., a current executive of the company) and we eliminate any potential candidates currently serving on the AC for the seat to be filled. Next, when assigning the machine-selected appointment for each company-year with an open AC seat being filled, we assume that each potential candidate will only accept one new board position in a given year. This assumption is based on historical, post-SOX appointment rates. Another key assumption in this process is that the model-assigned AC member is willing to serve on an AC. We expect there could be hesitations to serve on a company's AC due to perceptions of increased litigation risk associated with the overseeing the financial reporting process and because ACs are widely known to be the most time-intensive committee assignment in the board (Beasley et al. 2009; Brochet and Srinivasan 2014; KPMG 2015). We address this concern by repeating all analyses with a limited pool of potential candidates who are appointed to any other AC in years [t-3, t+3], relative to year t's appointment decision; that is, they are willing to serve on an AC *somewhere* and therefore understand the nature of the expected job duties. Regardless, it is still possible that some appointments deviate from expectations because the machine-selected candidate is not willing to serve. Despite this potential limitation of our methodology, our results are still useful in providing insights for potential directors, current nominating committee members, and regulators.

Our third key assumption is that we can identify a model suitable for predicting our measure of future performance (i.e., shareholder voting and ISS voting recommendations). The use of rolling five-year training windows is important because it allows our models to adapt to temporal changes in voting preferences and proxy advisor recommendation policies. To identify the best possible predictive models, we attempt OLS as well as four ML algorithms (elastic net, gradient boosting, neural networks, and random forest). The consideration of these different ML methods is appropriate in our setting because they can handle a large number of inputs, are not heavily biased by outliers, and allow for a mixture of linear and non-linear assumptions, as we discuss further in Section 3. We also attempt 14 different variations of measuring shareholder voting and ISS recommendations based on the three years following appointments in our out-of-sample training periods. From these combinations, we identify the measure and model combination that is best able to predict shareholder voting and ISS recommendations, respectively. Finally, to ensure that our results are not driven by one specific measure-model combination, we focus only on director characteristics that appear consistently under- or overweighted in both the full sample and the limited pool sample for both shareholder voting and ISS recommendation performance measures.

Our comparison of actual and machine-selected appointees suggests that nominating committees should be pulling directors with foreign experience, law degrees, greater network size, and greater concurrent private board seats *less* frequently than they currently are doing (i.e., these characteristics are over-weighted in current selection processes). In contrast, nominating committees should spend *more* time considering candidates with operating experience, CPA certification, gender diversity (female), and technology experience. These results are perhaps not surprising, given shareholder desires to increase board diversity and technical expertise. To put the potential gender bias in context, our models would assign a female AC member nearly twice as often as an actual appointment. Perhaps most surprising is that nominating committees are not appointing AC directors with core expertise often enough relative to the pool of potential directors and expected assignments. Specifically, CPA certification provides expertise related to financial reporting oversight, operating experience provides expertise related to internal audit oversight, and technology experience provides expertise related to growing needs in cybersecurity and internal controls over financial reporting.

To better understand whether these over- or underweighted characteristics ultimately impair the AC's ability to perform in the financial reporting oversight role, we classify actual appointments as "good" or "bad" based on the distance between predicted future performance for actual appointee director *j* and machine-selected appointee director *k,* and we examine future financial reporting failures for the company. We find that the occurrence of future misstatements is significantly higher for "bad" appointments compared to "good" appointments. Thus, higher deviations from machine-selected appointments have a real economic impact on financial reporting oversight.

Finally, to better understand the potential sources for these biases, we consider personal influence from the CEO or board, proxied for by previous connections, as well as whether the company is in a rush to fill the position, proxied for by whether the outgoing director is younger than the typical retirement age of a director. We find very little evidence that previous connections between a CEO and an actual appointee are associated with "bad" appointments. Instead, we find that the previous connections that are associated with "bad" appointments are those between the actual appointee and other board members. For one of our two measures of performance, we find evidence to suggest that when the outgoing member is younger, that is, not close to an expected retirement age in which succession planning is likely to occur, companies are more likely to make "bad" appointments.

These findings contribute to the literature examining specific AC characteristics by identifying characteristics that appear to be over- and underweighted in initial appointment decisions, relative to a large population of real potential directors. Our findings also contribute to the prior literature examining the nominating and board appointment process by utilizing OLS and ML as objective sorting mechanisms for potential director appointments. These findings should be of interest to shareholders casting votes in annual meetings and attempting to gain proxy access, to nominating committees responsible for board succession planning, and to regulators evaluating the efficacy of the current board appointment process. The findings are particularly timely given that turnover is increasing as a result of mandatory retirement ages and investors are calling for board refreshment (Gerut 2016a, 2018).

2. Background

2.1 Audit Committee Responsibilities

The AC is responsible for overseeing external audit, internal audit, and financial reporting processes (BRC 1999; SOX 2002). Traditional expectations of the AC include appointing, compensating, and evaluating external auditors, as well as overseeing management decisions related to accounting policies, earnings announcements, fraud risk assessment, internal controls, materiality, regulatory compliance, and taxes. However, the scope of their responsibilities is continuously expanding to cover other issues either directly or indirectly affecting financial reporting quality, such as the code of conduct, corporate culture, cybersecurity, emerging technologies, enterprise risk management, and whistleblower hotlines (Beasley et al. 2009; CAQ 2018; PwC 2018). "Investors look to audit committees with high expectations to establish and maintain the appropriate tone, capacity, and competence to oversee the quality of the financial reporting system" (Bricker 2017). To fulfill their responsibilities, many ACs perform annual self-assessments in an effort to continuously improve by benchmarking against peers and best practices and improving competencies within the committee through continuing education and board refreshment (Beasley et al. 2009).

Prior literature uses financial reporting quality to proxy for AC effectiveness and finds that the attributes of more effective ACs include the following: independence (Klein 2002; Carcello and Neal 2000; Klein 2002; Abbott et al. 2004; Anderson et al. 2004; Karamanou and Vafeas 2005; Chen et al. 2015), financial expertise (Abbott et al. 2004; Agrawal and Chada 2005; Dhaliwal et al. 2010; Bryan et al. 2013; Badolato et al. 2014), public accounting experience (Naiker and Sharma 2009), industry expertise (Cohen et al. 2014), legal expertise (Krishnan et al. 2011), and sufficient time to fulfill responsibilities (Sharma and Iselin 2012; Tanyi and Smith 2015).

2.2 Nominating Process

The Securities and Exchange Commission (SEC) and listing exchange rules define the independence, financial expertise, and evaluation requirements of directors that serve on the ACs of public companies (SOX 2002; SEC 2003; Morgan Lewis 2011). These same rules require that a committee of independent board members be responsible for the nomination process when a board position is to be filled. This committee is typically referred to as the nominating and governance committee, and although it is technically comprised of independent members, prior literature finds that CEOs continue to wield significant influence in the nomination process (Beasley et al. 2009; Carcello et al. 2011b; Cohen et al. 2013; Bruynseels and Cardinaels 2014; Clune et al. 2014; Lisic et al. 2016; Cassell et al. 2018).

Several published studies offer examples of CEO or director influence in the nominating process. In interviews of 42 AC members between 2004 and 2005, Beasley et al. (2009, 77) find that 33 percent of interviewees report having previous personal ties to management or other board members. They classify 19 percent of the interviewees' appointments as "ceremonial" because the director was selected due to this personal relationship. Cohen et al. (2013) interview 22 directors in late 2007 and find that 73 percent of interviewees report that the CEO "influenced" the selection of potential AC members, although the type of influence is admittedly nuanced. For example, one NYSE AC member suggests that CEOs are "very careful" with their involvement, while another NYSE AC member suggests the CEO has "a lot" of influence because it is "very important that the board have a congenial working relationship with management" (Cohen et al. 2013, 78). Clune et al. (2014, 779) interview 20 nominating committee members in 2010 and find that when making an initial pool of potential board candidates, "chemistry and comfort" between the board and the CEO is an important deciding factor for potential board candidates.[4] Interviewees report that candidates in the initial pool are most often nominated by other board members (78 percent), the CEO (50 percent), or other members of management (22 percent), with only 28 percent of interviewees reporting nominations coming from an independent search firm or consultant; the final candidate nominated by the committee is most often initially recommended by the CEO (36 percent) or another board member (36 percent), and only 21 percent of interviewees report final

[4] To further illustrate this point, in 2016, Armando Codina, chair of the nominating and corporate governance committee of the Home Depot board stated: "We have seen a number of people that have been interested in being on the board and others that have been proposed to us, and you know in a few minutes sometimes whether someone is going to work or not . . . There was one director . . . that was so full of himself that he would not have fit into our board" (Gerut 2016b). See also Bland (2019).

appointments that had been recommended by an independent search firm or consultant (Clune et al. 2014).

Board entrenchment can lead to resistance to change, which may entail resistance to finding optimal board candidates.[5] Deloitte's list of best practices for annual AC performance evaluations recognizes the potential risks of management involvement in appointing AC members: its first recommended question for self-assessment is whether "qualified audit committee members are identified by sources independent of management" (Deloitte 2018, 66). Even if the nominating committee makes final decisions based on a matrix of needed skills and backgrounds, the reliance on personal connections for the initial pool of candidates leaves room for ineffective pairings of potential AC members and companies. This concern is supported by archival evidence that ACs are less effective at monitoring financial reporting quality in the following conditions: when the CEO is involved in the nominating process (Carcello et al. 2011b), when CEO power is higher (Lisic et al. 2016), when AC members have friendship ties to the CEO (Bruynseels and Cardinaels 2014), or when there is a higher proportion of co-opted AC members (i.e., those appointed after the current CEO) (Cassell et al. 2018).

3. Research Design

To examine the AC appointment process, we use OLS and algorithms from ML to objectively select a candidate (i.e., the "machine-selected" appointment) based on predicted future performance of a large pool of potential candidates. The procedure, illustrated with a data flow diagram in Figure 1, can be sumarized as follows:

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[5] For example, in a resignation letter to the board of Asbury Automotive Inc., Scott Thompson writes (emphasis added): "The catalyst for my resignation is the Board's self-serving actions in not including me on the recommended slate of Asbury Directors for 2018 and the avoidance of ranking all director's qualifications, *including new candidates*, in an effort to rightsize the board and get the best and brightest leaders for Asbury Automotive, Inc." See https://www.sec.gov/Archives/edgar/data/1144980/000114498018000051/ex171letter.htm.

Step 1: Use iterative five-year training windows (t-5 through t-1) to estimate a predictive model for AC director performance as a function of company, AC, and director characteristics of actual appointments at company *i,* director *j* in year *t.* The first training window is 2003 to 2007; the last training window is 2010 to 2014. This step is completed up to 70 times (14 measures of performance * five potential models).[6]

Step 2: Save the parameter coefficients (OLS) or model of best fit (ML) from *Step 1* for the measure-model combinations that offer the best out-of-sample predictive power for a) shareholder voting and b) ISS recommendations, respectively.

Step 3: Using a dataset of all potential AC directors, director *k*, in year *t* who are not already serving on the AC of, or as an executive of, company *i*, use the parameters saved in Step 2 to predict future AC director performance for director *k* at company *i* based on election year *t*. The first year in which we machine-select director *k* for company *i* is 2008, based on the training window of 2003 to 2007. Next, we predict appointments in 2009 based on the training window of 2004 to 2008, and so on, up through appointments in 2015.

Step 4: For each company *i* with at least one new AC director appointed in year *t*, identify the machine-selected director *k* as the one with the highest predicted future AC director performance (i.e., highest predicted value of the measure of future performance). Director candidate *k* can only be appointed to one company in year *t*. If director *k* has the highest predicted performance of all potential director candidates at more than one company *i* in year *t*, we assign director *k* to the company where director *k* is predicted to have the strongest performance. The remaining companies then choose the director predicted to have the next-best performance, and so on. This results in the allocation of the best possible machine-selected director per company-year.

Step 5: Compare director characteristics between the actual appointment of director *j* and the machine-selected appointment of director *k* for company *i* and year *t*. In the case of more than one director appointed to an AC of company *i* in year *t* we compare each of the actual appointments to the one machine-selected AC director appointment for company *i* in the given year *t*.

3.1 Identifying Audit Committee Seats Open for Appointment

We begin with 29,477 new AC director *j* appointments between 2003 and 2015, inclusive, for public companies in BoardEx. We drop observations lost when merging BoardEx with Compustat, Audit Analytics, and the ISS Voting Analytics databases, and observations

[6] Certain measures and models perform so poorly that they do not actually converge.

missing specific data from the variables described further below, resulting in 8,027 new AC director *j* appointments for 2003 through 2015. The years 2003 to 2014, inclusive, are iteratively used as part of five-year training samples, which represents 7,441 unique company-director appointment-years. The years 2008 to 2015 represent 4,342 unique company-director appointment-years with which we predict the machine-selected director *k* based on the OLS or ML parameters established from the respective five-year training samples, and compare to the characteristics of the actual appointment *j*. The sample is described in further detail in Table 1.

3.2 Identifying Potential Audit Committee Members

For each company *i* with at least one AC director appointed in year *t*, we create a list of potential directors *k* using the listing of all active directors and executives in BoardEx, which includes both private and public companies. We include both private and public companies in the potential director set to include as broad of a range as possible. We exclude current executives at company *i* because this represents a violation of AC independence requirements, and we exclude any directors at company *i* already appointed to the AC because these are not eligible to fill the position up for appointment. This results in an average of approximately 35,000 unique potential candidates for each year in our sample, 2008 to 2015. Larcker and Tayan (2016) report that the United States has approximately 40,000 directors of large private and publicly traded corporations, suggesting that our identification of potential directors is comparable in size to the potential director market suggested by Larcker and Tayan (2016). We refer to this sample as the "full sample."

A key limitation of this approach is that some of these potential directors may be uninterested in serving on an AC of *any* company. 75 percent of AC members report a moderate to significant increase in workload in recent years and more than half report that the AC role is becoming “increasingly difficult” (KPMG 2015, 15), which may make it difficult for companies to find willing candidates. Top-performing board members are likely in high demand, and given that director pay is relatively constant across companies, directors may purposefully choose the assignment that provides the greatest pay for the lowest risk. Further, ACs are associated with higher litigation risk relative to other directors (Brochet and Srinivasan 2014), so it is possible that many qualified candidates choose not to serve on ACs despite being the most qualified people for the position. We therefore also report all analyses using a “limited pool” sample. In the limited pool sample, we require potential directors to have served on at least one AC at any point from t-3 through t+3, inclusive. We use three-year windows before or after predicted appointment in year t to capture the director’s general career interests and willingness to serve on any AC in this general time range. This results in an average of approximately 15,000 unique potential candidates for each year in our limited pool sample.

3.3 Measuring Audit Committee Director Performance

Relative to the AC’s fiduciary duty, company financial reporting quality is ultimately the strongest measure of AC performance. However, ACs are comprised of three to five members, on average (Tonello 2019), making individual performance difficult to model. To model AC director-specific performance, we use shareholder voting outcomes and ISS proxy advisor recommendations because they are director-specific and aggregate a variety of company-, committee- and director-specific factors to capture director performance (Fischer et al. 2009; Choi et al. 2010; Ertimur et al. 2015; Kachelmeier et al. 2016; Gal-Or et al. 2018).

On an annual basis, shareholders are provided the opportunity to vote on the appointment or re-appointment of individual directors. We consider both actual shareholder voting outcomes and proxy advisor recommendations because a large percentage of shareholders hold such large portfolios that individual analysis of voting decisions is too burdensome, leading them to outsource the research and investigation process to a proxy advisor (Choi et al. 2010; Yermack 2010). ISS is the largest proxy advisor, by far, and has been shown to have the most significant influence on shareholder voting (Cai et al. 2009; Ertimur et al. 2015). Because new AC members have a learning curve (Russell Reynolds Associates 2018), and because staggered boards may introduce variation in how often directors are up for a vote, we consider 14 different measures that capture shareholder voting and ISS recommendation data across t+1, t+2, and t+3. We use *future* voting outcomes and ISS recommendations because while we want the prediction for an appointment in year t to be based on AC and company characteristics known at the time of appointment in year t, actual performance for a specific director at a specific company is not known until after the director is appointed. Two of the 14 measures are described in detail in Appendix A; these are the two that perform the best in our prediction models (see Section 4.2).[7]

3.4 Predictors of Audit Committee Director Performance

We rely on prior literature examining the association between specific AC characteristics and financial reporting quality as well as evidence from actual board nomination processes to identify the AC director characteristics that we expect to be predictive of future performance, that is, shareholder voting and ISS voting recommendations. First, we consider whether the AC director has professional experience in accounting (*ACCTG_EXPER*), finance (*FINANCE_EXPER*), or public accounting (*PUBACCTG_EXPER*), or is licensed as a CPA (*CPA*), because these relate directly to ACs' need for financial expertise, which is associated

[7] The other twelve measures that we consider are linear and non-linear variations of these two measures: maximum of *VoteAgainst*; average and maximum of *ExcessVoteAgainst* (*VoteAgainst* for director *j* minus the average *VoteAgainst* for all other directors at company *i* in the same year); average and maximum of *VoteAgainst2* (same as *VoteAgainst* but ignores abstentions); average and maximum of *ExcessVoteAgainst2* (same as *ExcessVoteAgainst* but ignores abstentions); average and maximum of *HighVoteAgainst* (an indicator variable for the top decile of *VoteAgainst* in a given voting year); average and maximum of *HighVoteAgainst2* (same as *HighVoteAgainst* but ignores abstentions); and average of *ISSRecAgainst*.

with higher financial reporting quality (Abbott et al. 2004; Agrawal and Chada 2005; Naiker and Sharma 2009; Dhaliwal et al. 2010). We also consider whether the director is associated with a previous fraud, which has serious job market penalties (Srinivasan 2005; Fich and Shivdasani 2007; Brochet and Srinivasan 2014) (*PAST_FRAUD*). Due to growing demands for ACs to oversee issues such as cybersecurity, emerging technologies, general business risk, and regulatory compliance for increasingly multinational operations (e.g., Deloitte 2018), we also consider technology experience (*TECHNOLOGY_EXPER*), experience working outside of the United States (*FOREIGN_EXPER*), law experience (*LAW_EXPER*), and military experience (*MILITARY_EXPER*). We consider whether the AC director has experience in academia (*ACADEMIC_EXPER*), because prior literature finds that academic directors are appointed for their expertise, networks, and prestige (White et al. 2014). We consider whether the director has previous experience as a chief executive officer (*CEO_EXPER*), chief financial officer (*CFO_EXPER*), or chief operating officer (*COO_EXPER*), since these are the top three professional experiences sought after when recruiting board candidates (Larcker and Tayan 2016, referencing NACD 2009). We separately consider current executive experience (*CEO_CURRENT, CFO_CURRENT, COO_CURRENT*) because selections of currently-serving executives must balance the benefit of the experience with concerns about busyness.

Director networks represent a substantial benefit in terms of access to best practices and resources at other companies (Inintoli et al. 2018; Omer et al. 2019), therefore, we also consider past directorships or executive positions in the S&P 500 (*NB_DIRS_SP500*, *NB_JOBS_SP500*), and total network size as provided by BoardEx (*NETWORK_SIZE*). Given concerns about AC workloads (e.g., KPMG 2015; Tanyi and Smith 2015), we also consider contemporaneous workload obligations as a board member of another company (*NUM_BD_OTH_CO*, *NUM_PRIVATE_BOARDS*), and as a committee member of another company (*NUM_AC_OTH_CO, NUM_COMM_OTH_CO*), since committee positions hold higher workloads than general board membership, particularly the AC chair (*NUM_CHAIR_OTH_AC*). Because directors are sometimes appointed to the AC after they have already served on the board for a number of years, we consider whether the director is appointed to the AC in their first year on the board (*FIRST_YEAR*). Finally, we also consider demographic traits, such as age (*AGE*), gender (*FEMALE*), and education (*LAW_DEGREE, MBA, PHD, PRESTIGIOUS_INST*) since these socio-personal characteristics of directors have been found to have an impact on financial reporting quality (Srinidhi et al. 2011; Badolato et al. 2014) .

Given that governance is not a "one size fits all" solution, we include a wide variety of company characteristics that should impact the quality and level of oversight expertise needed on the AC, such as company size (*ASSETS*, *LN_ASSETS*, *LN_MKTVALUE, MKTVALUE*), complexity (*AR_INV*, *CO_AGE, COUNT_BUSSEG, COUNT_GEOSEG, FOREIGN, ISSUANCE, MERGER, RESTRUCTURE, SALES_GROWTH, SEO*), performance (*CFO, LEV, LOSS, MTB, ROA, VOL_CFO*), institutional ownership (*INST_OWN*), company reputation (Cao et al. 2012) (*CO_REPSCORE, MA_LIST*), board oversight (*AC_SIZE, BD_SIZE, BD_INDEP, RISK_ONLY*), CEO power (*CEO_DUALITY*, *CEO_TENURE*), and the characteristics of the other incumbent AC directors at time of appointment of the new director (*MEANAGE_OTHERDIRS, MEANFINEXP_OTHERDIRS, MEANFEM_OTHERDIRS, MEANTEN_OTHERDIRS*), as well as those of the external auditor (*AUD_BIG4, AUD_CLIENTIMP, AUD_FEES, AUD_OPIN, AUD_SPECIALIST, AUD_TENURE, AUD_TIER2*). Additionally, we include two-digit SIC code indicator variables to capture industry fixed effects. We also consider characteristics that are specific to director-company pairings, such as whether the director has previous or current industry experience related to the specific company (*NB_DIRS_SAMEIND*, *NB_BD_SAMEIND*), and geographic distance between the company and the director (*ZIP_DIST*).[8]

A key benefit of the ML, as opposed to other linear or non-linear estimation methods (e.g., ordinary least squares, logistic, etc.) is that many ML models do not require assumptions about functional form, nor are they impacted by potential confounding effects of multicollinearity between our variables. We therefore use several proxies for similar constructs (e.g., we use assets, market value, the natural log of assets, and the natural log of market value to capture various dimensions of company size). The full list of variables, definitions, and data sources used in our models is reported in Appendix A. The timing of variables is illustrated in Figure 2.

3.5 Machine Learning Algorithms

We begin with OLS, which is more traditionally used in accounting research. However, because functional form is unknown for the relationship between our company and AC characteristics and AC director performance, and because we have a large number of predictors that are potentially correlated, we also use four types of ML: elastic net, gradient boosting, neural networks, and random forest. Below, we explain each of the four ML algorithms used in our analyses.

Elastic Net Regression. Elastic net is a parametric model with linear assumptions. To understand how elastic net operates, consider that the error of a simple OLS model can be

[8] For each director, we use professional history to approximate geographic location. If the director has a full-time executive position, we use the geographic location of the director's full-time employment. If the director does not have a full-time position, we use the largest company for which there is a concurrent or recent directorship appointment, because this should approximate where the director spends a significant amount of time already. We calculate distance using the Vincenty (1975) ellipsoid distance formula, which is based on zip codes.

decomposed into three parts: bias, variance, and unexplainable error. It is well known that OLS produces unbiased estimates, but the variance of the estimates can be large whenever the inputs are highly correlated and when there are a large number of inputs, as is the case in our research question since the nomination process is largely a black box. Elastic net balances these concerns by introducing constraints that lower the variance while sacrificing some bias. This results in an overall lower total error and better out-of-sample predictions than OLS. The assumptions for elastic net are the same as OLS, but in settings with a large number of inputs, elastic net tends to perform better in out-of-sample prediction (Friedman et al. 2010). Thus, in our setting, with a large number of inputs, we expect elastic net to perform better than OLS. Elastic net requires all inputs to be scaled, so we scale all variables using a standard z-score standardization, where the predictor variables are demeaned and scaled by their standard deviation each year. For more information on the mechanics behind the elastic net regression (glmnet) algorithm in R, see Friedman et al. (2010).[9]

Gradient Boosting Regression. Gradient boosting is an ensemble method. Ensemble methods combine weak learners (simple models that perform poorly in isolation) to form an overall better prediction. Gradient boosting uses regression trees as its weak learners. Regression trees are decision trees that minimize the squared error and form real value predictions. Gradient boosting is an additive model, meaning that it forms a regression tree and the error is taken from this first tree. That error is used as the target for the next tree. Once the second tree is formed, it is added to the first tree. These two trees are used to form expectations and the error from these

[9] In short, elastic net combines ridge regression and least absolute shrinkage and selection operator (LASSO). Ridge regression penalizes the sum of squared coefficients and LASSO penalizes the sum of absolute values of coefficients. Ridge regression reduces the coefficients size (increasing bias) while simultaneously lowering the variance of the estimate. Small increases in bias could result in large decreases in variance and thus lower error. LASSO is similar to ridge regression, but LASSO allows for coefficients to equal zero (effectively selecting inputs), whereas ridge regression does not. Elastic net requires that the inputs be standardized, which is important because the ridge regression and lasso penalties are scale dependent.

combined trees is taken. A third regression tree is fit to the error from the first two combined trees. This process is repeated. Gradient boosting is a very powerful method, but it does have some weaknesses. It tends to over-fit noisy data due to sequentially fitting error terms. The parameters for the model of best fit, such as the number of rounds, number of splits each tree has, and the learning rate, are automatically set using cross-validation.[10] Gradient boosting offers the benefit of being a very efficient and accurate model, which also explains why it is one of the most popular models in ML competitions (e.g., Singh 2018, 2019). For more information on the mechanics behind the gradient boosting (XGBoost) algorithm in R, see Chen and Guestrin (2016).

Neural Networks Regression. Neural networks are based on models of the brain, where neurons are connected and learn from experience. Neural networks usually perform well when there is a complex relationship between the predictors and the outcome variable (in our case, ISS director recommendations). Neural networks work well with nonlinear data, with a large number of inputs, and with noisy data. They perform well due to their learning nature, but the final models of best fit are ultimately black boxes—opaque—which, coincidentally, is not unlike the nominating committee process. They can be computationally intense and need a fair amount of training data to perform well, which is one reason why we use five years of training data relative to each appointment year *t*. In our setting, neural networks offer the benefit of compensating for a large set of diverse measures that are potentially noisy (each of our measures are ultimately imperfect proxies for constructs such as company size and complexity, director expertise, etc.). For more information on the mechanics behind the neural networks regression (nnet) algorithm

[10] Instead of relying on assumptions by the programmer, machine learning attempts several possible combinations of tuning parameters and uses cross-validation to identify the ideal parameters as those that best fit the data. For more on cross-validation in machine learning, see, for example, Gupta (2017).

in R, see Venables and Ripley (2002).[11]

Random Forest Regression. Random forests are perhaps the easiest ML algorithm to understand and to implement. Random forests are a bagged combination of weak learners, that is, regression trees, where many decision trees combine to form a forest. Each regression tree is run on a random subset of the input variables on a bootstrapped sample of the training data. The random inputs for each tree in the forest forces the trees to not be correlated, which improves prediction. Random forests tend to run quickly, do not require inputs to be standardized, and have an easy to tune hyper-parameter. Random forests do have the drawback of tending to over-fit noisy data, which is another benefit of selecting the model of best fit using out-of-sample predictive power. For more information on the mechanics behind the random forest regression (randomForest) in R, see Liaw and Wiener (2002).

4. Results

4.1 Descriptive Statistics

Descriptive statistics for each new director position *j* for company *i* in year *t* are reported in Table 2. Director performance variables measured over time periods *t+1*, *t+2*, and *t+3* for director *j* are reported in Panel A. Characteristics for director *j* as of the time of the appointment are reported in Panel B. Characteristics for company *i*, year *t*, are reported in Panel C. Variables are as defined in Appendix A. The mean of *Avg_VoteAgainst* is 4.5 percent, which captures the average percent of shareholders voting against director *j* in the first three years of director

[11] In short, basic neural networks contain three layers: 1) the input layer, which consists of the input variables; 2) the hidden layer, which is a transformation of the inputs; and 3) the output layer, which contains the estimates. Inputs are first assigned random weights which are conceptually similar to coefficients in a linear regression. The sum of all of the weighted inputs are sent to each node in the hidden layer. A nonlinear activation function is applied in each node in the hidden layer. The output from each node in the hidden layer is then transformed and weights are again applied. This is then sent to the output layer. The error is examined and the weights are adjusted to lower the error and the inputs are sent through the network again with the updated weights. This is repeated until the model of best fit is established.

appointment. The mean of *Max_ISSRecAgainst,* our measure of whether ISS recommends a vote against director *j* in the first three years of the director's appointment, is 10.2 percent. These percentages are consistent with prior literature (e.g., Cai et al. 2009; Gal-Or et al. 2018; and Aggarwal et al. 2019).

On average, accounting and financial expertise of appointed AC members are as follows: 10.0 percent have accounting experience, 19.6 percent have finance experience, 15.1 have public accounting experience, 17.1 percent hold a CPA license, and 1.0 percent have been linked to a previous fraud. Technology experience (2.6 percent), law experience (3.2 percent), and military experience (3.0) have less representation among new appointees relative to academic experience (13.4 percent) or foreign operations experience (36.0 percent). New appointees are less likely to be current members of the C-suite (0.8, 4.6, and 1.0 percent for CEO, CFO, and COO, respectively), but prior experience in the C-suite is desired (18.1, 23.3, and 14.5 percent for CEO, CFO, and COO, respectively). The difference between current, as opposed to prior, C-suite experience is consistent with proxy advisor and shareholder concerns about workloads for current executives serving on outside boards (Cunningham et al. 2018). As for past experience as an executive or board member at an S&P 500 company, prior executive experience (0.489) is twice as common as prior board experience (0.253). On average, appointees are connected to 1,616 other professionals in the BoardEx network through current or former employment, board service, educational institution ties, and so on. Regarding contemporaneous workload on other boards, new appointees sit on an average of 0.802 other public company boards and 1.155 private company boards. On average, new appointees sit on 0.412 other ACs (chair at 0.163 other ACs) and 1.006 total committees at other firms. The average new AC appointee is 58 years old; 17.2 percent are female, 10.2 percent have completed law school, 40.6 percent have completed an MBA, 7.9 percent have completed a PhD, and 35.5 percent have a degree from a prestigious institution. Specific to the company-director pairing, new AC members are roughly equally likely to either have a past directorship or a past executive position in the same industry (0.216 and 0.227, respectively), and the director's home base is geographically close to the board. On average, the distance is 323 kilometers (201 miles), which is roughly the distance between New York and Boston. For 75 percent of the sample, the director's home base and the board are located less than 25 kilometers (15 miles) apart, which is roughly the distance between Dallas and Fort Worth. Close geographic proximity is consistent with nominating committees appointing a director who is already within the network of the current director and executive base.

The AC is typically comprised of four members, and the board is comprised of nine members. On average, 80.0 percent of the board is independent. The remaining company characteristics suggest that the appointments in our study represent a diverse set of company sizes, ages, profitability levels, complexity, and reputation.

In Table 3, we report descriptive statistics for the director characteristics in the potential director pool, both the full sample and the LP sample. We do not report statistics for industry expertise or distance since these are specific to a potential directorship pairing. Qualitatively, we observe that many of the characteristics in the potential director pool are comparable to those in the actual appointments, with a few notable exceptions. Compared to the potential pool of candidates, actual appointees exhibit greater female representation, larger networks, greater experience in the S&P 500, fewer commitments to concurrent outside board seats, and more experience as AC chairs at other companies. Without knowing which characteristics are associated with future performance, and thus which ones may be under- or overweighted relative to machine-selected appointments, these differences are merely descriptive observations about differences between potential director pools and AC appointments, on average.

4.2 Machine-Selected Director Appointments

As described in Section 3, we take each of the five-year training samples *t*-5 through *t*-1, beginning with 2003 to 2007 and ending with 2010 to 2014, and we use OLS and ML to estimate models of best fit between the appointed AC director characteristics and company characteristics at the time of the appointment with 14 measures of future director performance. Untabulated, we find that the most predictive models (using out of sample data) for shareholder voting and ISS recommendations are *Avg_VoteAgainst* and *Max_ISSRecAgainst*, respectively. In both cases, Elastic Net is the strongest performing model based on Diebold-Mariano tests for predictive accuracy for continuous variables (Diebold and Mariano 1995; Harvey et al. 1997) and the DeLong test for indicator variables (DeLong et al. 1988; Sun and Xu 2014).

Saving the model parameters from each measure-model, we use all potential director candidates available to company *i* with at least one open board seat in year *t* and predict each potential director *k*'s future performance. We classify the director with the highest predicted future performance for each company-year as the machine-selected appointee. We repeat this step using the limited pool of directors who have already indicated an interest in AC service *somewhere*. Table 4 reports the results of comparing the director characteristics of the actual appointment, director *j*, with the machine-selected appointment, director *k*. The mean actual appointment characteristics for director *j* are reported in the "Actual" column. Next, for each measure of performance, we report the mean characteristic for director *k* ("Pred.," i.e., prediction) as well as the differences between "Actual" and "Pred." The directional difference between "Actual" and "Pred." is shown with either "<" (the characteristic is underrepresented in the actual appointment) or ">" (the characteristic is overrepresented in the actual appointment). Whether the difference is statistically significant is represented with ***, **, or * for differences significant at $p < 0.01$, < 0.05, or < 0.10, respectively.

To ensure that we are only drawing inferences from those characteristics that are significantly associated with future performance in our out-of-sample training periods, we delete any cells where the characteristic is not in the top 20 characteristics used by the model. We use 20 as our cutoff to capture variables in approximately the top third of the distribution of "importance" to the performance model. Next, we want to ensure that inferences are not dependent on one specific measure of performance. We therefore require that a characteristic be important (i.e., in the top 20) for both measures examined, and we require that inferences remain the same across both measures, in both the full sample and the limited pool sample. We highlight in gray all characteristics that meet these screening requirements. We then summarize the total potential bias in terms of direction (< or >) and percent (%), where percent is calculated as the average differences in the full sample between "Actual" and "Pred." characteristics for those models where the characteristic is important. For brevity, we only report the directional sign of the difference for statistically significant differences ($p < 0.10$) in the limited pool sample.

Our comparison of actual and machine-selected appointments suggests that nominating committees appear to appoint directors with the following characteristics more often than predicted: foreign experience, law degree, and network potential (total network size as provided by BoardEx and number of concurrent private board seats). Our models suggest that nominating committees should be pulling from these characteristics *less* frequently than they are currently doing. In contrast, nominating committees should spend *more* time considering candidates with operating experience (COO), CPA certification, gender diversity (female), and technology experience.

Economically, the largest differences between actual and machine-selected appointments relate to law degrees (*LAW_DEGREE*, 317%) and the number of concurrent boards (*NUM_PRIVATE_BOARDS*, 284%). The most economically underweighted differences relate to technology experience (*TECHNOLOGY_EXPER, -75%*), and CPA certification (*CPA, -57%*). Because we are using actual directors and executives in BoardEx's database, all of these conclusions have already taken into consideration the question of whether there is physically a director with these characteristics available to take these AC roles. Whether these directors would actually take these appointments is beyond the scope of our models, but we believe these concerns are alleviated in part because we focus on the results that draw the same inferences when using the limited pool sample.

4.3 Future Financial Reporting Quality

Our models are trained to predict shareholder voting outcomes and ISS voting recommendations, director-specific measures of performance. To determine whether differences between actual and machine-selected appointments have real economic consequences to companies, we calculate the difference between the model-predicted performance of the actual appointee, and the model-predicted performance of the machine-selected appointee, based on observable data as of the appointment in year *t*. High differences between predicted performance suggest "bad" appointments and low differences suggest "good" appointments. We use four different sample cuts to see how bad appointments compare to good appointments: the 20^{th} percentile compared to the 80^{th} percentile, the 30^{th} percentile compared to the 70^{th} percentile, the

40th percentile compared to the 60th percentile, and below the median compared to above the median.

In Table 5, for each of these sample cuts, we report the mean value of *AvgBigR*, which is the average misstatement rate in the three years following director *j*'s actual appointment at company *i* in year *t* (i.e., a value of 0.000 suggests no misstatements in the three years, a value of 0.333 suggests one of three years has a misstatement, and a value of 1.000 suggests all three years are misstated). If our models are able to help distinguish "good" appointments from "bad" appointments, we expect the rate of future misstatement to be higher in the "bad" appointment group relative to the "good" appointment group. Our findings suggest that our models are indeed capable of separating good appointments from bad appointments, because we find significant differences in misstatement rates for all of the sample cuts, across both of our measures of performance.

4.4 Potential Sources of Bias in Appointments

Connections between Director j and the Board and CEO. Prior literature finds that board members and CEOs wield significant influence in identifying the initial pool of candidates in the nomination process, leading to potentially impaired independence for AC members (Westphal and Zajac 1995; Beasley et al. 2009; Carcello et al. 2011b; Cohen et al. 2013; Bruynseels and Cardinaels 2014; Clune et al. 2014; Lisic et al. 2016; Cassell et al. 2018). To examine whether differences between actual and machine-selected appointments observed in our study are associated with ties between the appointment of director *j* and the CEO or other board members, we use BoardEx to identify overlaps in employment or director history between actual appointee director *j* and the CEO, the chair of the board, the nominating committee, and the board in general. We calculate *PredictedDirectorPerformance* for both actual director *j* and machine-selected director *k.* We expect that connections lead to greater deviations from machine-selected appointments, which should result in higher differences in *PredictedDirectorPerformance* between director *j* and director *k.* As reported in Table 6, Panel A, and consistent with this expectation, we observe higher differences between director *j* and director *k* when the actual appointee has previous connections to the chair of the board, the nominating committee, or the board in general. Surprisingly, we find very little evidence that significant differences in model-predicted future performance arise when there are previous connections to the CEO, suggesting that the bias observed in our study is more likely due to previous connections with the board, and not the CEO.

Rush to Fill the Audit Committee Seat. Most director appointments occur to replace a director who has recently departed from the board. In many cases, the departure of the previous director is expected and a succession plan is likely in place. However, in some cases, the departure of the previous director is unexpected. Previous research documents that after unexpected director departures, it takes six months, on average, to nominate a replacement director (Nguyen and Nielsen 2010). Replacing a director involves search costs and comes with a learning curve for the newly appointed director. Because of this, firms have an incentive to replace a director who has unexpectedly departed from the board as soon as possible. Firms may have to rush to fill an AC seat that has unexpectedly opened up and this may result in higher deviations of the actual appointed director from the predicted best director.

To examine whether differences between the actual and machine-selected appointments observed in our study are associated with a rush to replace a previous director who departed unexpectedly, we analyze the age of the director who departed in the year before the appointment of director *j*. Similar to Nguyen and Nielsen (2010), we argue that younger directors are less likely than older directors to depart from the board. We thus separate director appointments that replace an outgoing director into two groups based on whether the previous director is less than 62 years old of age. This represents the average age of AC directors in their last year of service across the entire BoardEx database. Directors who are appointed to replace previous directors of an age lower than 62 are categorized as unexpected replacements, suggesting a potential rush to fill the seat. As reported in Table 6, Panel B, we do find some evidence that a rush to find a replacement AC director leads to higher deviations in predicted performance between director *j* and director *k*; specifically when ISS recommendations are the measure of performance.

5. Conclusion

We use objective models to machine-select AC appointments from a pool of tens of thousands of potential board candidates based on OLS and machine learning predictions of future performance. Our results suggest that companies may be placing too much emphasis on demographics such as legal experience, foreign operations experience, network size, and number of private boards served on. In contrast, nominating committees should be paying more attention to CPA licensure, technology experience, gender diversity, and operating experience. We find that when differences in predicted future performance between actual appointees and machine-selected appointees are higher, the company is more likely to misstate their financial statements in the three years following appointment, relative to appointments where differences in predicted future performance are lower. This suggests that there are real economic consequences to financial reporting quality when nominating committees deviate from objective appointment decisions. Deviations from machine-selected characteristics are higher when there are stronger connections between the actual appointee and the board, or when there is a rush to fill the position, proxied for by the age of the outgoing AC member.

Some of our results are particularly interesting given current trends in practice. For example, consistent with concerns in practice for more diversity on boards, our models suggest that females are appointed to ACs approximately half as often as we predict. Because our data use current directors and executives from BoardEx as the potential pool of candidates, a lack of sufficient supply of female candidates is not a valid explanation for why boards appoint females half as often as expected in our models. Additional research is needed to better understand gender roles in board appointment and performance. Another interesting implication is in the workload of actual versus machine-selected appointments. Consistent with calls from proxy advisors and shareholders for board members to limit concurrent service obligations, we find that companies are more likely to appoint directors with higher concurrent board service than our models would predict (specifically, higher concurrent private board experience). Our models predict that these "busy" potential directors should be appointed to ACs less often than they currently are, presumably because of the busyness effect with concurrent responsibilities (e.g., Sharma and Iselin 2012; Tanyi and Smith 2015). Thus, our finding contributes to a literature stream that finds mixed results on the effect of busyness on board performance (e.g., Carcello and Neal 2003; Sharma and Iselin 2012; Tanyi and Smith 2015; Castonguay 2019). Finally, our findings suggest that when there are stronger connections between an actual appointee and the board, that appointee is predicted to have worse performance relative to actual appointees at companies that have weaker or no connections between the appointee and the board. Thus, our findings call on nominating committees to reevaluate the practice of starting with current connections to identify potential candidate pools (Clune et al. 2014).

Our inferences are subject to two important limitations. The first is that we use shareholder voting outcomes and ISS against recommendations as proxies for director performance at a specific company. We recognize that prior literature has raised concerns about the efficacy and quality of these votes and recommendations (Larcker et al. 2015; Hayne and Vance 2019; Malenko and Malenko 2019). We are not aware, however, of any other director-specific characteristics that could proxy for performance. Compensation and meeting attendance capture inputs to director performance, and they are largely fixed relative to firm-specific policies. Thus, they are unlikely to capture cross-sectional variation in the quality of the director's performance. We therefore believe that shareholder voting and ISS recommendations are the best publicly available proxies for director-specific performance. Future research is needed to identify other potential measures of director-specific performance relative to assigned committee or directorship expectations, such as individual AC directors' contributions to maintaining strong financial reporting quality.

The second important limitation on our inferences is that our results cannot disentangle whether mismatches are due to bias in the appointment process (i.e., insufficient research in looking for potential candidates) or due to an unwillingness of qualified candidates to fill certain board seats. We assume that the machine-selected candidate is always willing to serve on a specific company's AC and draw inferences from the nominating committee perspective. Regardless of this assumption, however, our findings should still be useful to practice because mismatches suggest that either nominating committees are not willing to search enough to find optimal candidates, or nominating committees are not willing to pay enough for the optimal candidate to satisfy their individual risk preferences. Additional research is needed to better understand potential misalignments between actual and machine-selected appointments from the perspectives of both nominating committees and potential board candidates.

In summary, our results suggest that companies are likely misweighting key criteria when making AC appointment decisions, and that the resulting mismatches can have real economic impacts on financial reporting quality. Additional research is needed to better understand the nominating process and to identify ways to mitigate potential mismatches, such as hiring consulting agencies. Our findings should be of interest to potential board members, regulators, and shareholders by shedding light on potential ineffectiveness in the current appointment process.

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Appendix A
Variable definitions

Director Future Performance (relative to election year *t* for company *i* and director *j*)

Max_ISSRecAgainst	Maximum value of *ISSRecAgainst* for director *j* among years *t+1*, *t+2*, and *t+3*. *ISSRecAgainst* is an indicator variable equal to one if the appointed director *j* receives a vote against recommendation from ISS in a given year, and zero otherwise (ISS Voting Analytics)
Avg_VoteAgainst	Average of *VoteAgainst* for director *j* among years *t*+1, *t*+2, and *t*+3. *VoteAgainst* is equal to the percentage of votes cast against, abstaining, or withheld from a director in a given year [Against + Abstain + Withheld) / (Against + Abstain + Withheld + For] (ISS Voting Analytics)

Director Characteristics (year *t* for company *i* and director *j*/*k* unless specified otherwise)

ACADEMIC_EXPER	Indicator variable equal to one if past non director role includes one of the following, and zero otherwise: "Professor" "Economist" "Academic" Lecturer" "Instructor" "Faculty" "Dean" "Fellow" (BoardEx)
ACCTG_EXPER	Indicator variable equal to one if past non director role includes one of the following, and zero otherwise: "Accounting" "Accountant" "Controller" "CAO" (BoardEx)
AGE	The age of age of the director (BoardEx)
CEO_CURRENT	Indicator variable equal to one if the director has a current non director role includes "CEO," and zero otherwise (BoardEx)
CEO_EXPER	Indicator variable equal to one if past non director role includes "CEO," and zero otherwise (BoardEx)
CFO_CURRENT	Indicator variable equal to one if the director has a current non director role including includes "CFO," and zero otherwise (BoardEx)
CFO_EXPER	Indicator variable equal to one if past non director role includes "CFO," and zero otherwise (BoardEx)
COO_CURRENT	Indicator variable equal to one if the director has a current non director role includes "COO," and zero otherwise (BoardEx)
COO_EXPER	Indicator variable equal to one if past non director role includes "COO," and zero otherwise (BoardEx)
CPA	Indicator variable equal to one if director holds a CPA designation, and zero otherwise (BoardEx)
FEMALE	Indicator variable equal to one if director is a female, and zero otherwise (BoardEx)

FINANCE_EXPER	Indicator variable equal to one if past non director role includes one of the following, and zero otherwise: "Underwriter" "Investment" "Broker" "Banker" "Banking" "Economist" "Finance" "treasurer" "Financial" "Actuary" "Floor Trader" Equity" "Market Maker" "Hedge Fund" (BoardEx)
FIRST_YEAR	Indicator variable equal to one if the AC director is appointed to the AC when they join the board, and equal to zero if they are rotated to the AC after initial board appointment
FOREIGN_EXPER	Indicator variable equal to one if director has past work experience in a country outside of the United States (BoardEx)
LAW_DEGREE	Indicator variable equal to one if director holds a J.D. degree or LL.M. degree, and zero otherwise (BoardEx)
LAW_EXPER	Indicator variable equal to one if past non director role includes one of the following, and zero otherwise: "Lawyer" "Legal" "Attorney" "Judge" "Judicial" (BoardEx)
MBA	Indicator variable equal to one if director holds an MBA degree, and zero otherwise (BoardEx)
MILITARY_EXPER	Indicator variable equal to one if past non director role includes one of the following, and zero otherwise: "Captain" "Soldier" "Lieutenant" "Admiral" "Military" "Commanding" "Commander" "Infantry" "Veteran" "Sergeant" "Army" (BoardEx)
NB_DIRS_SAMEIND	Number of past directorships at companies in the same industry sector as the directorship (BoardEx)
NB_DIRS_SP500	Number of past directorships at companies in the S&P 500 index (BoardEx)
NB_JOBS_SAMEIND	Number of past full time positions at companies in the same industry sector as the directorship (BoardEx)
NB_JOBS_SP500	Number of past full time positions at companies in the S&P 500 index (BoardEx)
NETWORK_SIZE	Network size of director (number of overlaps with other individuals in BoardEx through employment, education, and other activities) (BoardEx)
NUM_AC_OTH_CO	Number of AC memberships the director currently holds at other companies (BoardEx)
NUM_BD_OTH_CO	Number of boards the director is currently serving on at other companies (BoardEx)
NUM_CHAIR_OTH_AC	Number of current AC chair positions at other companies (BoardEx)

NUM_COMM_OTH_CO	Number of committees the director is currently serving on at other companies (BoardEx)
NUM_PRIVATE_BOARDS	Number of boards the director is currently serving on at privately held companies (BoardEx)
PAST_FRAUD	Indicator variable equal to one if the director was previously on the board of a company with a fraud that resulted in a restatement in the past ten years, and zero otherwise (BoardEx/Audit Analytics)
PHD	Indicator variable equal to one if director holds a Ph.D. degree, and zero otherwise (BoardEx)
PRESTIGOUS_INST	Indicator variable equal to one if director attended an elite institution of higher education (as designated by Finkelstein 1992), and zero otherwise (BoardEx)
PUBACCTG_EXPER	Indicator variable equal to one if past non director role includes working for a public accounting firm (Big four and the next four), and zero otherwise (BoardEx)
TECHNOLOGY_EXPER	Indicator variable equal to one if past non director role includes one of the following, and zero otherwise: "Technology" "Software" "Programmer" " IT " "Chief Information Officer" "Database" "System Administrator" "Developer" (BoardEx)
ZIP_DIST (km)	Distance between the zip code of the director's home base and the zip code of the company on which they serve as an AC director, in kilometers (km). Home base and distance calculations are further described in Section 3 (BoardEx)

Company Characteristics (year *t* for company *i* unless specified otherwise)	
AC_SIZE	Number of members on AC (BoardEx)
AR_INV	Receivables and inventory, divided by total assets [(RECT+INVT)/AT] (Compustat)
ASSETS	Total assets (AT) (Compustat)
AUD_BIG4	Indicator variable equal to one if the auditor is from the Big 4, and zero otherwise (Audit Analytics)
AUD_CLIENTIMP	Total fees paid by firm *i* to the auditor in year *t* divided by the total revenue of the auditor local office that issues that issues the audit report. (Audit Analytics)
AUD_FEES	Total fees paid by firm *i* to the auditor in year *t* (Audit Analytics)
AUD_OPIN	Auditor's opinion on the company's financial statements in year *t*. [1= Unqualified; 2= Qualified; 3=No opinion; 4=

	Unqualified with additional language; 5= Adverse opinion] (Compustat)
AUD_SPECIALIST	Indicator variable equal to one if the auditor has the largest market share of a two-digit SIC category in the local city and if its market share is at least 10% greater than the second largest industry leader in the local city's audit market, and zero otherwise (Reichelt and Wang 2010) (Audit Analytics)
AUD_TENURE	Number of years the company has been audited by the current audit firm (Compustat/Audit Analytics)
AUD_TIER2	Indicator variable equal to one if the auditor is a second tier auditor, and zero otherwise (Audit Analytics)
BD_INDEP	Proportion of the board that is independent, measured as the number of independent directors divided by board size (BoardEx)
BD_SIZE	Board size, measured by number of board members (BoardEx)
CEO_DUALITY	An indicator variable equal to one if the CEO is also the chair of the board of directors, and zero otherwise (BoardEx)
CEO_TENURE	Tenure of the CEO (BoardEx)
CFO	Cash flow from operations scaled by total assets (OANCF/AT) (Compustat)
CO_AGE	The natural log of years the firm has existed in Compustat (Compustat)
CO_REPSCORE	A firm's reputation score in year t as measured by Fortune's Most Admired Company List (Fortune; Cao et al. 2012)
COUNT_BUSSEG	The number of business segments (Compustat)
COUNT_GEOSEG	The number of geographic segments (Compustat)
FOREIGN	Indicator variable equal to one if firm has foreign operations (FCA not equal to zero and not missing), and zero otherwise (Compustat)
INST_OWN	Percentage of shares held by instituional investors (Thomson Reuters)
ISSUANCE	Indicator variable equal to one if company issued debt (current year total debt (DLTT+DLC) is greater than 105 percent of prior year total debt), and zero otherwise (Compustat)
LEV	Long term debt divided by total assets [(DLTT+DLC)/AT] (Compustat)
LN_ASSETS	Natural logarithm of total assets [log(AT)] (Compustat)
LN_MKTVALUE	Natural logarithm of market value [log(PRCC_F*CSHO)] (Compustat)

LOSS	Indicator variable equal to one if the firm reports a net loss (NI less than zero), and zero otherwise (Compustat)
MA_LIST	Indicator variable equal to one if the firm is on Fortune's Most Admired Company list in year t, and zero otherwise (Fortune)
MEANAGE_OTHERDIRS	Mean age of all other directors on the AC (excludes the appointed director)
MEANFINEXP_OTHERDIRS	Proportion of all other directors on the AC that qualify are designated financial experts (excludes the appointed director)
MEANFEM_OTHERDIRS	Proportion of all other directors on the AC that are female (excludes the appointed director)
MEANTEN_OTHERDIRS	Mean tenure of all other directors on the AC (excludes the appointed director)
MERGER	Indicator variable equal to one if firm is involved in mergers or acquisitions (if AQA is not equal to zero or missing), and zero otherwise (Compustat)
MKTVALUE	Market value [PRCC_F*CSHO)] (Compustat)
MTB	Market-to-book[(PRCC_F*CSHO)/CEQ] (Compustat)
RESTRUCTURE	Restructuring charges in year t scaled by total assets in year t [(RCA)/AT] (Compustat)
RISK_ONLY	Indicator variable equal to one if the firm has a standalone risk committee (BoardEx)
ROA	Net Income divided by average total assets [NI/((AT_{t-1}+AT)/2)] (Compustat)
SALES_GROWTH	Year-over-year sales growth [(SALE- $SALE_{t-1}$) / $SALE_{t-1}$] (Compustat)
SEO	Indicator variable equal to one if stock is issued during the year (if SCSTKC variable is greater than zero), and zero otherwise (Compustat)
VOL_CFO	Volatility of cash flows. Measured as standard deviation of variable CFO over years [t-4 to t-1] (Compustat)

Future Financial Reporting Quality (for company *i*, relative to appointment in year *t*)

Avg_BigR	Average of *BigR* for company *i* in years *t+1*, year *t+2* and year *t+3* relative the appointment of director *j* in year *t. BigR* is an indicator variable equal to one if the company's financial statements in a given year are later restated as announced through an 8-K item 4.02. (Audit Analytics Non-Reliance)

Figure 1
Data flow diagram of data analysis

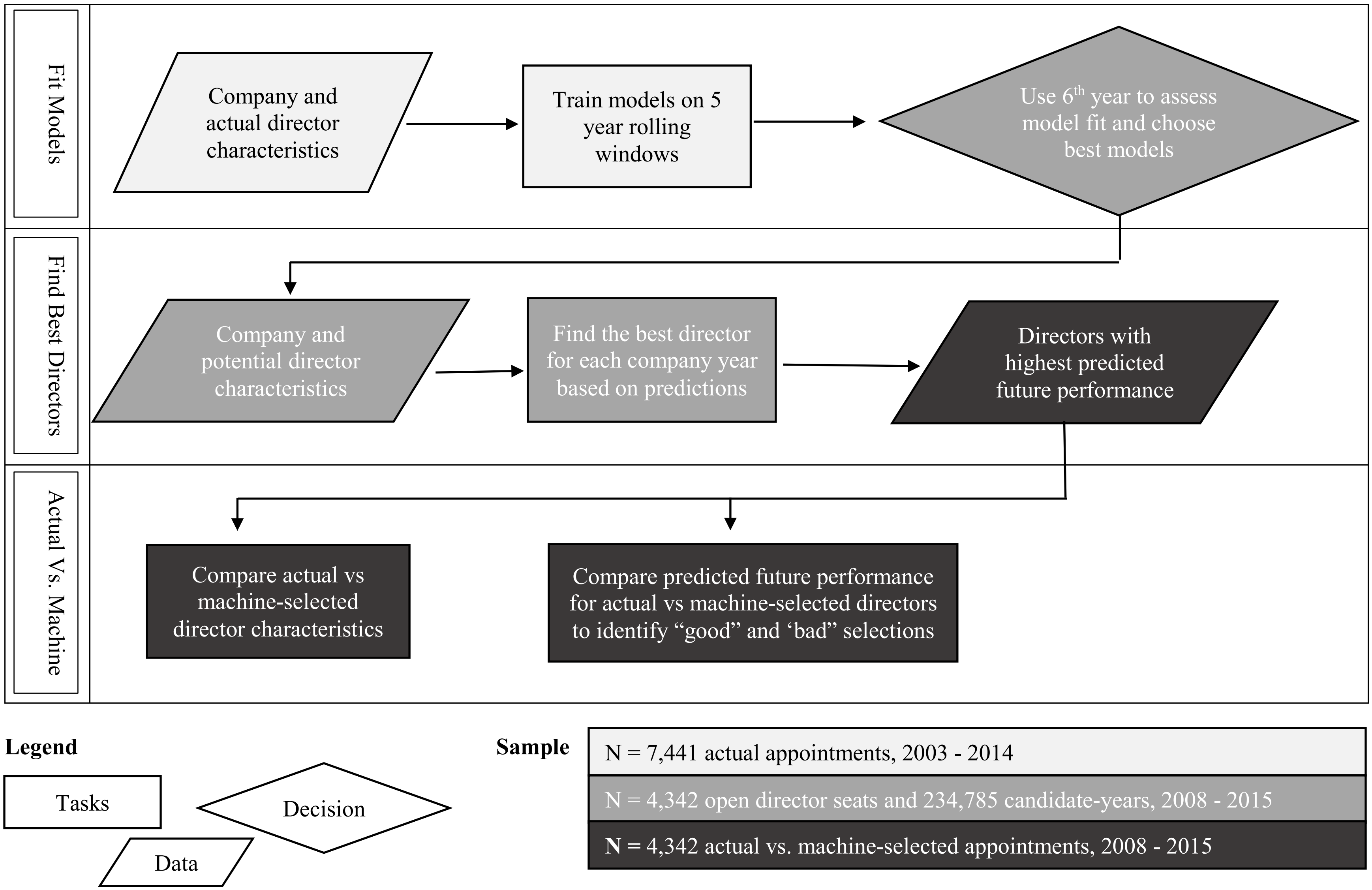

Figure 2
Illustrative timeline of variables

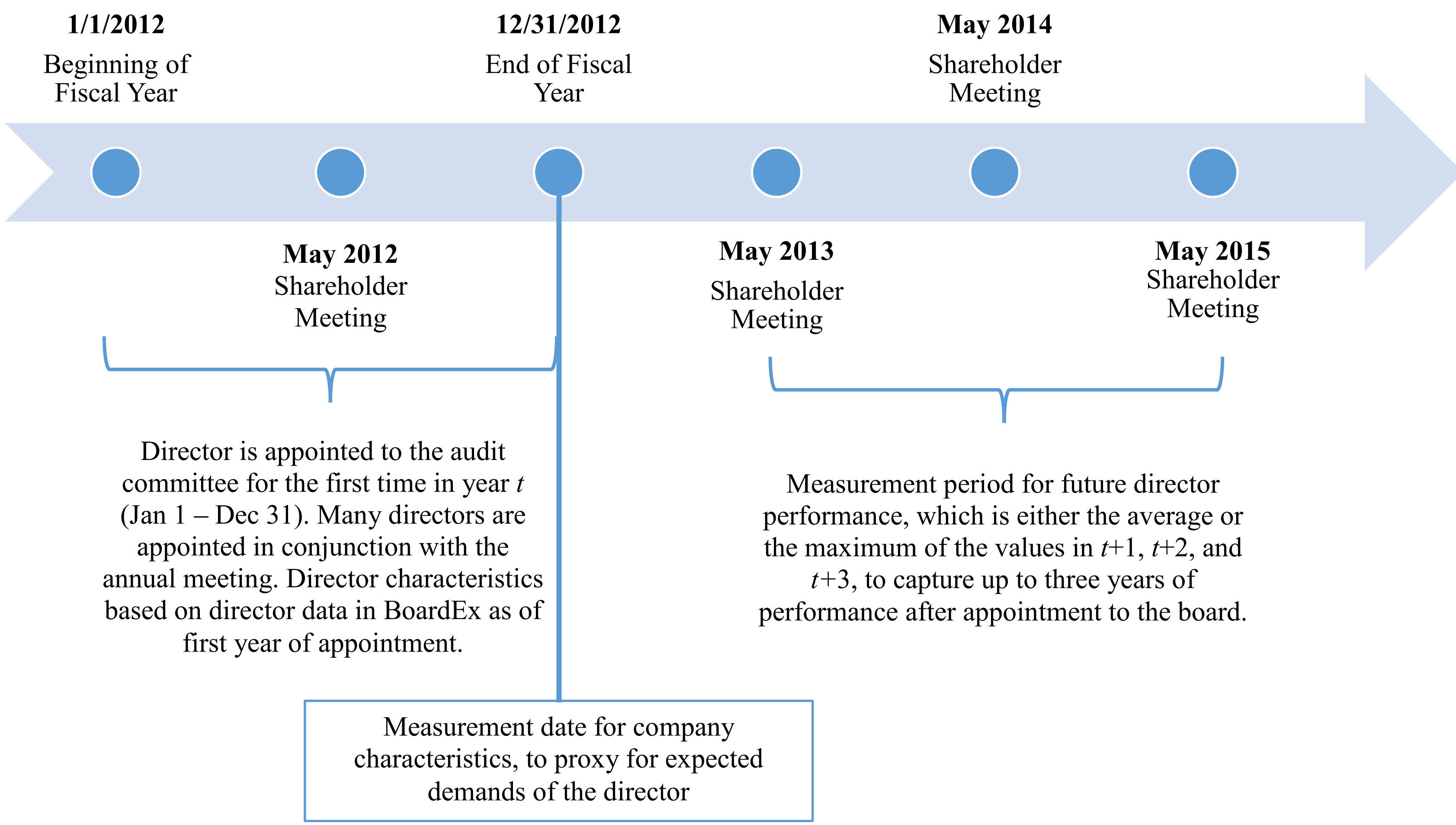

Table 1
Sample selection

Director Performance Prediction Sample	Observations
New AC director appointments 2003- 2015 in BoardEx	29,477
Less: observations lost when merging to Compustat	(2,727)
Less: observations lost when merging to Audit Analytics	(1,323)
Less: observations lost when merging to ISS Voting Analytics	(15,816)
Less: observations data for variables in Table 1	(1,584)
Final sample of new AC director appointments, 2003 – 2015	8,027
AC Director-company-years in training samples, 2003 - 2014	7,441
AC Director-company-years in ML prediction sample, 2008 - 2015	4,342

Table 2
Descriptive statistics, AC director appointments 2003 – 2015

Panel A: Director performance measures

	Mean	St. Dev.	25th	Median	75th
Avg_VoteAgainst	0.045	0.064	0.011	0.022	0.049
Max_VoteAgainst	0.067	0.095	0.014	0.030	0.073
Max_ISSRecAgainst	0.102	0.303	0.000	0.000	0.000
N = 8,027					

Panel B: Director characteristics

	Mean	St. Dev.	25th	Median	75th
ACADEMIC_EXPER	0.134	0.341	0.000	0.000	0.000
ACCTG_EXPER	0.100	0.300	0.000	0.000	0.000
AGE	58.024	7.740	53.000	58.000	63.000
CEO_CURRENT	0.008	0.088	0.000	0.000	0.000
CEO_EXPER	0.181	0.385	0.000	0.000	0.000
CFO_CURRENT	0.046	0.210	0.000	0.000	0.000
CFO_EXPER	0.233	0.423	0.000	0.000	0.000
COO_CURRENT	0.010	0.101	0.000	0.000	0.000
COO_EXPER	0.145	0.352	0.000	0.000	0.000
CPA	0.171	0.376	0.000	0.000	0.000
FEMALE	0.172	0.377	0.000	0.000	0.000
FINANCE_EXPER	0.196	0.397	0.000	0.000	0.000
FOREIGN_EXPER	0.360	0.480	0.000	0.000	1.000
LAW_DEGREE	0.102	0.303	0.000	0.000	0.000
LAW_EXPER	0.032	0.177	0.000	0.000	0.000
MBA	0.406	0.491	0.000	0.000	1.000
MILITARY_EXPER	0.030	0.172	0.000	0.000	0.000
NB_DIRS_SAMEIND	0.216	0.606	0.000	0.000	0.000
NB_DIRS_SP500	0.253	0.635	0.000	0.000	0.000
NB_JOBS_SAMEIND	0.227	0.557	0.000	0.000	0.000
NB_JOBS_SP500	0.489	0.757	0.000	0.000	1.000
NETWORK_SIZE	1,616.780	1,636.397	513.500	1,151.000	2,197.000
NUM_AC_OTH_CO	0.412	0.723	0.000	0.000	1.000
NUM_BD_OTH_CO	0.802	1.042	0.000	0.000	1.000
NUM_CHAIR_OTH_AC	0.163	0.472	0.000	0.000	0.000
NUM_COMM_OTH_CO	1.006	1.618	0.000	0.000	2.000
NUM_PRIVATE_BOARDS	1.155	1.885	0.000	1.000	2.000
PAST_FRAUD	0.010	0.101	0.000	0.000	0.000
PHD	0.079	0.269	0.000	0.000	0.000
PRESTIGOUS_INST	0.355	0.479	0.000	0.000	1.000

PUBACCTG_EXPER	0.151	0.359	0.000	0.000	0.000
TECHNOLOGY_EXPER	0.026	0.159	0.000	0.000	0.000
ZIP_DIST (km)	323.586	820.483	0.000	0.000	25.359
N = 8,027					

Panel C: Company characteristics

	Mean	St. Dev.	P25	Median	P75
AC_SIZE	4.206	1.141	3.000	4.000	5.000
AR_INV	0.258	0.205	0.089	0.215	0.364
ASSETS (millions)	17,110.630	89,989.640	547.334	2,016.127	7,117.493
AUD_BIG4	0.895	0.307	1.000	1.000	1.000
AUD_CLIENTIMP	0.107	0.171	0.014	0.041	0.115
AUD_FEES (thousands)	3,525.941	6,926.284	750.763	1,486.000	3,492.150
AUD_SPECIALIST	0.233	0.423	0.000	0.000	0.000
AUD_TENURE	14.462	10.379	6.000	12.000	20.000
AUD_TIER2	0.044	0.205	0.000	0.000	0.000
AUD_OPIN	2.070	1.437	1.000	1.000	4.000
BD_INDEP	0.800	0.111	0.730	0.833	0.889
BD_SIZE	9.671	2.474	8.000	9.000	11.000
CEO_DUALITY	0.512	0.500	0.000	1.000	1.000
CEO_TENURE	4.978	5.480	1.300	3.300	6.700
CFO	0.073	0.128	0.032	0.077	0.131
CO_AGE	27.511	17.538	13.000	21.000	42.000
CO_REPSCORE	0.982	2.354	0.000	0.000	0.000
COUNT_BUSSEG	6.256	5.762	3.000	3.000	10.000
COUNT_GEOSEG	6.778	7.504	2.000	4.000	9.500
FIRSTYEAR	0.635	0.481	0.000	1.000	1.000
FOREIGN	0.288	0.453	0.000	0.000	1.000
INST_OWN	0.695	0.211	0.570	0.730	0.853
ISSUANCE	0.362	0.480	0.000	0.000	1.000
LEV	0.234	0.221	0.054	0.195	0.346
LN_ASSETS	7.666	1.896	6.305	7.609	8.870
LN_MKTVALUE	7.480	1.686	6.254	7.328	8.546
LOSS	0.192	0.394	0.000	0.000	0.000
MA_LIST	0.151	0.358	0.000	0.000	0.000
MEANAGE_OTHERDIRS	61.678	5.458	58.500	62.000	65.200
MEANFINEXP_OTHERDIRS	0.532	0.300	0.300	0.500	0.800
MEANFEM_OTHERDIRS	0.135	0.189	0.000	0.000	0.200
MEANTEN_OTHERDIRS	7.337	4.159	4.363	6.775	9.600
MERGER	0.449	0.497	0.000	0.000	1.000
MKTVALUE (millions)	8,588.480	27,550.330	520.102	1,522.509	5,143.569
MTB	3.213	26.327	1.351	2.089	3.504

RESTRUCTURE	-0.002	0.012	-0.001	0.000	0.000
RISKONLY	0.097	0.296	0.000	0.000	0.000
ROA	0.024	0.148	0.008	0.038	0.081
SALES_GROWTH	0.625	41.325	-0.013	0.069	0.178
SEO	0.043	0.203	0.000	0.000	0.000
VOL_CFO	0.050	0.086	0.014	0.029	0.055
N = 8,027					

All variables are as defined in Appendix A.

Table 3
Descriptive statistics, potential director candidate pools 2008 – 2015

	Full Sample N = 234,785		**Limited Pool Sample N = 110,620**	
	Mean	**Std Dev**	**Mean**	**Std Dev**
ACADEMIC_EXPER	0.108	0.310	0.130	0.336
ACCTG_EXPER	0.121	0.326	0.083	0.277
AGE	58.136	9.979	60.825	9.193
CEO_CURRENT	0.031	0.174	0.007	0.085
CEO_EXPER	0.179	0.383	0.170	0.375
CFO_CURRENT	0.144	0.351	0.038	0.191
CFO_EXPER	0.241	0.428	0.200	0.400
COO_CURRENT	0.048	0.214	0.008	0.089
COO_EXPER	0.152	0.359	0.121	0.326
CPA	0.169	0.374	0.164	0.370
FEMALE	0.099	0.299	0.109	0.312
FINANCE_EXPER	0.203	0.402	0.171	0.377
FOREIGN_EXPER	0.358	0.479	0.369	0.483
LAW_DEGREE	0.105	0.307	0.115	0.319
LAW_EXPER	0.039	0.194	0.042	0.200
MBA	0.329	0.470	0.355	0.478
MILITARY_EXPER	0.024	0.154	0.030	0.170
NB_DIRS_SP500	0.110	0.434	0.167	0.534
NB_JOBS_SP500	0.322	0.632	0.335	0.656
NETWORK_SIZE	851.729	985.102	898.403	986.883
NUM_AC_OTH_CO	0.459	0.715	0.959	0.773
NUM_BD_OTH_CO	1.082	0.931	1.443	1.019
NUM_CHAIR_OTH_AC	0.041	0.323	0.086	0.465
NUM_COMM_OTH_CO	1.265	1.672	2.185	1.890
NUM_PRIVATE_BOARDS	1.165	1.982	1.403	2.083
PAST_FRAUD	0.009	0.095	0.012	0.110
PHD	0.076	0.265	0.085	0.279
PRESTIGOUS_INST	0.286	0.452	0.322	0.467
PUBACCTG_EXPER	0.134	0.340	0.131	0.338
TECHNOLOGY_EXPER	0.019	0.137	0.017	0.131

All variables are as defined in Appendix A.

Table 4
Summary of potential biases in audit committee appointments

				Best Model = ElasticNet				***Best Model = ElasticNet***				
	Conclusion			***DV = Avg_VoteAgainst***				***DV = Max_ISSRecAgainst***				**Limited Pool**
	Bias	**%**	**Actual**	**Pred.**	**Diff**	**Sig**	**T-value**	**Pred.**	**Diff**	**Sig**	**T-value**	**Sample**
ACADEMIC_EXPER			0.13									_ / _
ACCTG_EXPER			0.10					0.18	<	***	-11.61	_ / <
AGE			58.59	45.67	>	***	74.96					> / _
CEO_CURRENT			0.01									_ / _
CEO_EXPER			0.21									_ / _
CFO_CURRENT			0.04	0.52	<	***	-59.78					< / _
CFO_EXPER			0.22					0.44	<	***	-22.98	_ / <
COO_CURRENT			0.01					0.67	<	***	-91.20	_ / <
COO_EXPER	<	*-49%*	0.16	0.21	<	***	-6.69	0.61	<	***	-50.34	< / <
CPA	<	*-57%*	0.16	0.37	<	***	-23.64	0.37	<	***	-23.95	< / <
FEMALE	<	*-43%*	0.19	0.34	<	***	-17.02	0.33	<	***	-15.64	< / <
FINANCE_EXPER			0.19					0.30	<	***	-13.33	_ / <
FOREIGN_EXPER	>	*40%*	0.36	0.31	>	***	4.71	0.22	>	***	14.99	> / >
LAW_DEGREE	>	*317%*	0.10	0.02	>	***	17.00	0.03	>	***	15.45	> / >
LAW_EXPER			0.03									_ / _
MBA			0.40	0.48	<	***	-7.15					< / _
MILITARY_EXPER			0.03					0.00	>	***	8.82	_ / >
NB_DIRS_SAMEIND			0.25	0.03	>	***	18.84					> / _
NB_DIRS_SP500			0.26									_ / _
NB_JOBS_SAMEIND			0.25	5.94	<	***	-15.77					< / _
NB_JOBS_SP500			0.51	0.69	<	***	-10.11	0.46	>	***	3.33	< / ns
NETWORK_SIZE	>	*43%*	1,619.94	1,138.33	>	***	16.98	1,119.34	>	***	16.25	> / >
NUM_AC_OTH_CO			0.37					0.17	>	***	9.14	_ / <
NUM_BD_OTH_CO			0.77	0.37	>	***	23.11	0.32	>	***	14.03	> / <
NUM_CHAIR_OTH_AC			0.12					0.11	>	ns	0.38	_ / <
NUM_COMM_OTH_CO			0.93					0.51	>	***	5.72	_ / <
NUM_PRIVATE_BOARDS	>	*284%*	1.16	0.36	>	***	27.30	0.26	>	***	31.00	> / >
PAST_FRAUD			0.01	0.00	>	***	6.53					> / _
PHD			0.08	0.05	>	***	4.98					> / _
PRESTIGOUS_INST			0.35									_ / _

PUBACCTG_EXPER			0.14	0.30	<	***	-18.41					< / _
TECHNOLOGY_EXPER	<	*-75%*	0.03	0.11	<	***	-15.30	0.13	<	***	-17.41	< / <
ZIP_DIST (km)			322.38	2,290.50	<	***	-83.14					< / _

This table presents univariate differences in means of director-level characteristics using actual appointments for the company-years appointing a new AC director *j* in year *t* between 2008 and 2015 and the model-assigned ('machine-selected') AC director *k* in year *t*. Empty cells indicate that the characteristic is not an important predictor for that specific performance measurement variable. We require the characteristic to be one of the top 20 predictors to be an important characteristic. Shaded characteristics are those where inferences remain the same across both measures of director performance in both the full sample (main table) and the Limited Pool Sample, which is where we restrict the pool of potential directors as those who sit on an AC at any publicly traded company at least once between *t*-3 and *t*+3. The percent of bias is calculated as the average difference between director *j* and director *k* characteristics. < (>) indicates that the actual appointments underweight (overweight) the respective characteristic. For brevity, when reporting results for the Limited Pool Sample, we only report the directional bias (> or <) when differences between actual director *j* and limited-pool predicted director *k* are statistically significant (i.e., p-value < 0.10). _ indicates that the difference is not statistically significant (i.e., p-value > 0.10) or the variable is not a top-20 predictor in the limited pool sample. ***, **, and * indicate that the difference in means between the actual and machine-selected appointment is statistically significant (two-tailed) at 0.01, 0.05, and 0.10, respectively. Variables are sorted alphabetically. All variables are defined in Appendix A.

Table 5
Association between deviations from expectations and future misstatements

High (Low) = Top (Bottom)	***Avg_BigR*** $_{t+1,t+2,t+3}$ — ***Director Performance = AvgVoteAgainst*** — **Deviations from Expectations**				***Director Performance = MaxISSRecAgainst*** — **Deviations from Expectations**				**Limited Pool Sample**
	High	***Low***	***Diff***	***T-value***	***High***	***Low***	***Diff***	***T-value***	
20% of sample	0.034	0.020	**	2.05	0.038	0.013	***	3.66	*** / ***
30% of sample	0.032	0.020	**	2.04	0.037	0.020	***	2.81	** / ***
40% of sample	0.031	0.022	**	1.95	0.037	0.018	***	3.72	** / ***
50% of sample	0.031	0.023	**	1.80	0.035	0.020	***	3.18	** / ***

This table presents the mean of future misstatement rates (*Avg_BigR* $_{t+1,t+2,t+3}$) relative to appointment year *t* for both the portion of the sample with low deviations from expectations (i.e., low differences between predicted performance for the actual and machine-selected appointment) and high deviations from expectations (i.e., high differences between predicted performance for the actual and machine-selected appointment). For brevity, when reporting results for the Limited Pool Sample, we only report the p-value; directional differences (i.e., *High* > *Low*) remain the same as in the main sample. Limited Pool Sample is as defined in Table 4. ***, **, and * indicate that the difference in means between the *High* and *Low* groups is statistically significant (one-tailed) at 0.01, 0.05, and 0.10, respectively. All variables are defined in Appendix A.

Table 6
Potential causes for observed differences

Panel A: Previous connections between the company and director *j*

	Mean Differences in Predicted Performance between Director *j* and Director *k*								
	Director Performance = AvgVoteAgainst				*Director Performance = MaxISSRecAgainst*				
	Connections				**Connections**				**Limited Pool**
Type of Connection	*Yes*	*No*	*Diff*	*T-value*	*Yes*	*No*	*Diff*	*T-value*	**Sample**
CEO	0.025	0.024	ns	0.61	0.068	0.066	ns	0.98	ns / **
Chair of the Board	0.027	0.024	*	1.32	0.068	0.065	*	1.40	* / **
Nominating Comm	0.028	0.023	***	2.53	0.070	0.065	**	2.31	*** / ***
Board Director, Any	0.027	0.022	***	3.28	0.068	0.064	***	2.74	*** / ***

Panel B: A rush to fill the open position

	Mean Differences in Predicted Performance between Director *j* and Director *k*								
	Director Performance = Avg_VoteAgainst				*Director Performance = Max_ISSRecAgainst*				
	Rush to Fill Position				**Rush to Fill Position**				**Limited Pool**
	Yes	*No*	*Diff*	*T-value*	*Yes*	*No*	*Diff*	*T-value*	**Sample**
Yes (No) Rush to Fill Open Position Based on Outgoing Director Age < (>=) 62	0.023	0.024	ns	-0.27	0.069	0.062	***	3.20	ns / ***

This table presents univariate differences of $PredictedDirectorPerformance_j$ - $PredictedDirectorPerformance_k$. *PredictedDirectorPerformance* is equal to the value obtained for a director when we input company *i*, year *t*, director characteristics into the respective out-of-sample training model. In Panel A, we classify potential connections with the CEO, chair of the board, nominating committee directors, or board directors (any), by comparing executive and director employment histories for each of these respective roles at company *i*, year *t*, to the newly appointed director *j*. We use all available history in BoardEx as of the year prior to appointment. In Panel B, we classify rush to fill as those seats where the exiting director was < 62 years old because across the full dataset of directors in BoardEx between 2003 and 2015, in the last year that a director serves on an AC, his age is 62 on average. Less than the average age is more likely to be an unexpected departure, and thus there is more of a rush to fill the position, leading to potentially weaker appointment decisions. More than or equal to the average is more likely to be an expected departure, where the nominating committee has more time to find a suitable replacement, leading to stronger appointment decisions. For brevity, when reporting results for the Limited Pool Sample, we only report the p-value; directional differences (i.e., *Yes* > *No*) remain the same as in the main sample. Limited Pool Sample is as defined in Table 4. ***, **, and * indicate that the difference in means between groups is statistically significant (one-tailed) at 0.01, 0.05, and 0.10, respectively. All variables are defined in Appendix A.