Thirty Years of Change: The Evolution of Classified Boards

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Abstract

We create a novel classified (staggered) board database covering all U.S. public firms from 1991 to 2020 and document significant differences in classified board usage over a firm's life cycle depending on the decade the firm is aging or the year it goes public. While classified boards were rarely removed in the 1990s, firms that aged or went public during the following decades were more likely to declassify as they matured. Increased institutional ownership and scrutiny on governance appear to have contributed to this more dynamic adjustment over time, which recent theory predicts and our valuation analyses corroborate is value-maximizing.

Keywords: Corporate governance, Takeover defenses, Classified (staggered) boards, Life cycle, Machine learning, IPO cohorts

JEL Classifications: C81, D22, G23, G30, G34

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THIRTY YEARS OF CHANGE: THE EVOLUTION OF CLASSIFIED BOARDS*

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August 1, 2023

Abstract

We create a novel classified (staggered) board database covering all U.S. public firms from 1991 to 2020 and document significant differences in classified board usage over a firm's life cycle depending on the decade the firm is aging or the year it goes public. While classified boards were rarely removed in the 1990s, firms that aged or went public during the following decades were more likely to declassify as they matured. Increased institutional ownership and scrutiny on governance appear to have contributed to this more dynamic adjustment over time, which recent theory predicts and our valuation analyses corroborate is value-maximizing.

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1. Introduction

In a seminal survey paper, Shleifer and Vishny (1997) argue that a successful corporate governance system combines significant legal protection of shareholder rights with an important role for large investor ownership. At the time, many viewed the United States (U.S.) corporate governance system as embodying these elements. However, a wave of corporate scandals in the early 2000s raised serious concerns about U.S. governance practices, leading to considerable changes over the next two decades that attempted to improve the corporate governance landscape (e.g., Madden, 2011; Kastiel and Nili, 2021). Another notable change was the substantial growth in institutional ownership, especially by passive investors, that resulted in increased ownership concentration and institutional investors playing a more prominent role in corporate governance.

In this paper, we explore the impact of these changes on firm-level corporate governance decisions by examining whether the use of takeover defenses over a firm's life cycle has evolved over the last 30 years. A recent study finds that takeover defenses are valuable for newly public firms but that their costs outweigh their benefits as firms mature (Johnson, Karpoff, and Yi, 2022), implying that value-maximizing behavior entails younger firms employing takeover defenses initially and then shedding the defenses as they age. However, prior work generally concludes that firms rarely remove defenses due to high collective action costs and free-riding problems among shareholders (e.g., Hannes, 2006; Johnson, Karpoff, and Yi, 2022). We hypothesize that increases in shareholder rights protection, more concentrated institutional investor ownership, and other changes during the most recent decades have pressured firms that go public or age over this period to adjust their takeover defenses more dynamically over their life cycle.

To study how takeover defense usage over a firm's life cycle has changed, we build a novel dataset that tracks the classified (staggered) board status of nearly all U.S. publicly traded firms over the last three decades. Under a classified board structure, directors are separated into classes serving staggered terms, with only one class standing for reelection each year. Because the typical classified board structure includes three distinct classes, each serving three-year terms, incumbent directors have significant protection against removal or control attempts via proxy fights or takeover bids (e.g., Bebchuk, Coates, and Subramanian, 2002; John, Kadyrzhanova, and Lee, 2021), leading some researchers to conclude that classified boards are among the most powerful defenses available to firms (e.g., Klausner, 2013; Daines, Li, and Wang, 2021).[1]

Studying how classified board usage over a firm's life cycle has evolved over the last 30 years poses several empirical challenges. In particular, investigating whether certain cohorts of firms, defined by a shared decade or initial public offering (IPO) year, use classified boards differently as they age requires a comprehensive dataset that tracks firms over their full life cycle. Most prior studies use data from the Institutional Shareholder Services (ISS) Governance database (formerly known as the RiskMetrics and IRRC databases and hereafter referenced as ISS). However, this database is limited to more mature and successful firms in the S&P 1500 Composite Index and does not include data for the years before or after a firm is added or removed from the Index. Thus, the ISS database does not capture the full life cycle of firms, nor does it reflect how most public firms not in the S&P 1500 Index choose their governance practices.

We overcome these sampling limitations by constructing a new dataset that contains the classified board status for almost all U.S. publicly traded firms between 1991 and 2020.[2] We generate this dataset using a multi-faceted approach that combines a machine learning technique, the Random Forests (RF) Classifier, with textual analysis and manual inspection. Thus, while our paper focuses on studying how classified board usage over a firm's life cycle has changed over time, we also contribute to the literature by providing a framework for expanding existing databases using innovations in machine learning and by making this data available for others.

RF Classifier is a popular machine learning technique (Varian, 2014). It grows many decision trees, with each tree bootstrapping the number of observations in a training set and selecting a random number of predictors at each decision node to grow the tree to the largest extent possible.

[1] The entrenchment index is another common takeover defense measure (Bebchuk, Cohen, and Ferrell, 2009). However, studies find that it includes provisions (e.g., golden parachutes, poison pills) that are ineffective for deterring takeovers (see Karpoff and Wittry (2023) for a review). As an example, prior work argues that poison pills have lost their importance as a deterrent because most firms have a "shadow pill" that allows them to adopt an explicit pill at any time without shareholder approval (e.g., Catan and Kahan, 2016). Another provision not included in the entrenchment index but commonly studied is the dual-class share structure (e.g., Gompers, Ishii, and Metrick, 2010). We do not consider dual-class shares because only a small percentage of public firms have this defense.

[2] We detail the construction of our dataset in Section 2.2 and the Internet Appendix, and our code and data are available at https://sites.google.com/utk.edu/matthew-serfling/data.

Each tree then gives a classification, and the forest chooses the classification with the highest accuracy. In our first step, we obtain the optimal classification for classified boards using training and testing samples from the ISS database. Next, we extend the algorithm to all U.S. public firms utilizing the electronic annual proxy filings available on SEC EDGAR. We combine our machine learning approach with manual inspection to ensure data accuracy. For the years before EDGAR's implementation, we hand-collect classified board data from microfiche filings. Lastly, we manually collect information on classified boards for IPO years using each firm's last prospectus before its IPO. In total, our new classified board dataset includes about three times the number of firm-year observations compared to existing databases.

With this novel dataset, we document several new findings. First, classified board usage has changed substantially over the past 30 years. The fraction of firms with classified boards increased during the 1990s, starting at 41% in 1991 and peaking at 56% in 2003. However, from that point onward, the fraction of firms with a classified board steadily declined to 44% by 2020. The decline was especially sharp for firms in the S&P 500 (1500) Index, decreasing from 60% (59%) in the early 1990s to 12% (31%) in 2020.[3] Conversely, for firms not in the S&P 1500 Index, 42% had a classified board in the early 1990s, and 52% of firms had one in 2020. These results indicate that trends observed using commercial databases like ISS do not reflect how most U.S. firms have used classified boards over time. We also find that, over our entire sample period, 57% of firms aged 0-1 had a classified board, but this percentage falls to 44% for the most mature firms aged ≥16.

Second, and the key finding of our study, the use of classified boards across a firm's life cycle varies significantly over time. Throughout the 1990s, classified board usage only slightly declined as firms aged. This pattern is consistent with the view that takeover defenses tend to be sticky and infrequently adjusted as firms age. However, between 2001 and 2010, there was a steady decline in the use of classified boards as firms aged from 65% for the youngest firms to 46% for the most mature. The life cycle effect is even more pronounced between 2011 and 2020, when 73% and 33% of the youngest and most mature firms had a classified board, respectively. We reach a similar

[3] The sharp decrease in the use of classified boards among S&P 500 firms after 2010 coincided with the Harvard Law School's Shareholder Rights Project that pushed for many of these firms to declassify their boards.

conclusion when we split the sample by IPO cohorts. The earliest cohort of IPO firms in our sample were more likely to keep a classified board as they aged, whereas the most recent IPO cohort rapidly declassified their boards as they matured. We also observe similar decade and IPO cohort effects when we examine declassification rates instead. Overall, these results highlight substantial decade and IPO cohort effects in how firms use classified boards over their life cycles.

Third, we investigate what could have contributed to the trends in how firms use classified boards. We first explore whether changes in the nature of firms or the market for corporate control can explain our results. Over the past 30 years, firms have grown larger and increasingly rely on intangible assets, among other differences (e.g., Kahle and Stulz, 2017). However, even after controlling for time-varying firm characteristics and industry fixed effects, the patterns we observe in the use of classified boards persist. The patterns also hold after controlling for firm fixed effects, where trends are derived from within-firm variation (Cremers, Litov, and Sepe, 2017). Further, while takeover activity has changed over time, these changes appear across all firm-age groups. Thus, changes in firm characteristics and the market for corporate control are unable to explain the decade and IPO cohort life cycle effects we observe in classified board usage.

Next, we examine whether our main hypothesis that a structural change in attitudes toward the costs and benefits of classified boards, greater attention to corporate governance, and a shift to more concentrated ownership by institutional investors contribute to the change in how firms use classified boards across different periods. We find that news articles and academic studies on governance and classified boards sharply increased after the accounting scandals in the early 2000s. We also find significant increases in institutional ownership, especially by passive index funds that cannot exit their positions (i.e., "Wall Street walk") if they are displeased with a firm's governance practices and thus must engage with management to advocate for changes. Further consistent with a shift in sentiment against classified boards and increased shareholder involvement, more firms with classified boards received proposals to declassify beginning in the early 2000s, and average voting support in favor of declassifying continued to rise over time.

We also find that among mature firms, the relation between having a classified board and institutional investor ownership turned negative during the most recent decade. Similarly, mature firms that are larger or in the S&P 1500 Index only became more likely to declassify their boards during the last decade. In contrast, this attention effect is absent among young firms. Moreover, in a matched sample difference-in-differences analysis, we show that firms, especially mature firms, only began declassifying their boards after being added to the S&P 1500 during the most recent decade. Overall, these results are consistent with changes to the U.S. corporate governance system and lower collective action costs for institutional shareholders pressuring firms in more recent years to shed their classified boards more quickly as they age. Nevertheless, because we do not have a valid instrumental variable or natural experiment for each of these mechanisms, we acknowledge that linking trends in classified boards to trends in other outcomes does not establish a causal effect, and the results should be interpreted accordingly.

Fourth, we explore the relation between classified boards and firm value. Further consistent with increased attention and changing attitudes towards governance over time, market responses to firms declassifying their boards became significantly positive beginning in 1999-2000. We also examine the association between classified boards and Tobin's Q. In a frictionless world, firms should dynamically adjust their use of classified boards to maximize value. However, due to high collective action costs and free-riding problems among shareholders, these adjustments often do not happen, rendering takeover defenses sticky. This stickiness produces a positive association between firm value and defenses for young firms and a negative association for mature firms (Johnson, Karpoff, and Yi, 2022). Consistent with this life cycle-based value reversal, we find that in the 1990s and 2000s, classified boards added value to newly public firms but decreased value among older firms. Conversely, this pattern disappeared in the 2010s when firms became more likely to declassify as they aged. These results imply that, as governance scrutiny and institutional ownership increased over time, the frictions that had historically impeded firms from adjusting their classified boards optimally over their life cycle lessened by the most recent decade.

Our paper makes several contributions to the literature. First, using our comprehensive dataset, we uncover new facts that shed light on the evolution of classified board usage among U.S. firms over the past three decades, demonstrating a time-varying life cycle effect on board structure choices. Recent work finds that the percentage of firms that go public with a classified board has increased over time and that this increase appears to be an optimal governance choice (Field and Lowry, 2022). Our findings add to this literature by showing how firms have adapted their use of classified boards over their full life cycle and how these adaptations vary by decade and IPO cohort. Further, we show how changes to the attention and scrutiny of governance practices and increases in institutional ownership likely contributed to these patterns over time. Thus, our results have important implications for understanding the factors that affect board structures and the progression of the U.S. corporate governance system over the last 30 years.

Second, our paper is related to a growing finance literature studying the importance of cohort effects. Many papers examine how belonging to a cohort, such as those arising from shared experiences, economic environments, and IPO timing, affects asset allocation and risk-taking decisions (e.g., Malmendier and Nagel, 2011, 2016; Malmendier, Tate, and Yan, 2011; Bekaert, Hoyem, Hu, and Ravina, 2017; Parker, Schoar, Cole, and Simester, 2022), employment outcomes and managerial styles (Oyer, 2008; Schoar and Zuo, 2017; Law and Zhou, 2021), acquisition decisions (Arikan and Stulz, 2016), and the value of cash (Bates, Chang, and Chi, 2018). Most closely related to our study within this literature, Karpoff, Schonlau, and Wehrly (2017, 2022) construct geography and IPO cohort-based instruments to study the effect of takeover defenses on acquisition likelihood. Our paper contributes to these studies by providing insights into how firms adjust their governance practices and board structures depending on the prevailing corporate governance environment during the decade the firms are aging or at the time of their IPO.

Third, we extend the literature exploring the relation between classified boards and firm value. Our paper speaks most directly to the findings in Johnson, Karpoff, and Yi (2022) that because takeover defenses are rarely adjusted by firms over their life cycle, defenses add value when firms are young and destroy value as they mature. We add new insights to this literature by showing that this value reversal effect has diminished over time as firms have become more likely to declassify their boards as they age, resulting in an equilibrium relation between classified boards and firm value. Our paper is also related to prior work that finds mixed results on whether classified boards are good or bad for shareholders (e.g., Bebchuk and Cohen, 2005; Faleye, 2007; Cohen and Wang, 2013; Cremers and Ferrell, 2014; Amihud and Stoyanov, 2017; Cremers, Litov, and Sepe, 2017;

Daines, Li, and Wang, 2021) and suggests that previous results may depend on the views, attitudes, and attention to classified boards over the sample period studied.

Lastly, we make a methodological contribution by demonstrating how machine learning can be used to construct new datasets that offer better representations of sample populations. While machine learning is applied in the finance literature (e.g., Gu, Kelly, and Xiu, 2020; Bianchi, Büchner, and Tamoni, 2021; Erel, Stern, Tan, and Weisbach, 2021; Li, Mai, Shen, and Yan, 2021), it has been primarily used for measuring latent variables (e.g., risk premiums, culture) and predicting financial returns and firm performance. To the best of our knowledge, we are the first to use machine learning to overcome the sampling limitations of a commercial database. We apply this methodology to classified boards, but future work can adapt our approach to other settings.

The rest of the paper is organized as follows. Section 2 discusses our data. Section 3 examines trends in classified boards. Section 4 investigates potential explanations for these trends. Section 5 examines the relation between classified boards and firm value. Section 6 concludes.

2. Data and Methodology

2.1. Data sources

This study utilizes several sources of data. We construct our base sample from the CRSP-Compustat merged database over the 30-year period from 1991 to 2020. We obtain data on stock returns from CRSP, accounting data from Compustat, and institutional ownership data from Thomson-Reuters Institutional (13-F) Holdings. To implement our machine learning algorithm that identifies the classified board status of all firms, we build a training sample using information available in the ISS database. ISS tracks the classified board status of firms in the S&P 1500 Index from 1990 to 2020, except for 2017 when the sample expanded to the Russell 3000 Index. From 1990 to 2006, ISS collected data every two to three years. Beginning in 2007, ISS collected this data annually. There is no backward or forward data filling by ISS once a firm is added or removed from the S&P 1500. In our sample, only 28.8% of firms are in the S&P 1500 index.

As inputs in our machine learning algorithm, we obtain annual proxy statements (DEF 14A filings) from the SEC EDGAR system from as early as 1993. The first year that all firms are required to file proxy statements through electronic filings on the SEC EDGAR system is 1996. Thus, as we detail in the following sections, we also hand-collect classified board information for firms from 1991 to 1995 from microfiche DEF 14A filings.

2.2. Collecting classified board data from EDGAR filings

2.2.1. Overview of RF Classifier

RF Classifier is a supervised machine learning algorithm used in modeling predictions and built on decision trees. The RF Classifier is a collection of decision tree classifiers. It is an updated classification algorithm to the common decision tree models proposed by Breiman (2001) and later implemented by Liaw and Wiener (2002). Compared to traditional models, RF Classifier has three main advantages. First, RF Classifier is based on the bagging algorithm and uses an ensemble learning technique. Intuitively, RF Classifier can create many trees on the subset of the data and combine the output of all the trees. As a result, it reduces the high variance problem associated with a single decision tree and thus improves accuracy. Second, unlike a single tree that considers all the features at once and offers only one path, RF Classifier creates multiple trees with random features, increasing efficiency and making it easier to handle large datasets. Finally, RF Classifier does not require parametric assumptions on the functional form among predictors and outcomes.

The RF Classifier methodology has been successfully used in various science fields and, recently, in economics and business. For example, RF Classifier outperforms other statistical tools in predicting future ecological changes, provides the most accurate prediction of chemical compound classifications, achieves a high degree of accuracy in 3D object recognition, and has better properties in predicting microarray data (Svetnik et al., 2003; Díaz-Uriarte and de Andrés, 2006; Prasad, Iverson, and Liaw, 2006; Shotton et al., 2013). In economics, Varian (2014) advocates using RF Classifier in econometrics, and Bajari, Nekipelov, Ryan, and Yang (2015) use RF Classifier to estimate demand functions. More recently, Frankel, Jennings, and Lee (2022) show that RF Classifier better captures disclosure sentiment than alternative machine learning techniques, and Miric, Jia, and Huang (2023) find that RF Classifier is the best-performing machine learning classifier to identify artificial intelligence technologies in patents.

2.2.2. Estimation steps and machine learning prediction

One of the main contributions of our study is to demonstrate a novel use of machine learning that uses data from an existing database to extrapolate data points with a high degree of accuracy to firms not in the database. Our procedure builds on and formalizes the approach in Guernsey, Sepe, and Serfling (2022) and is detailed in the Internet Appendix. We obtain all DEF 14A filings in SEC EDGAR to implement the RF Classifier algorithm, producing 179,942 unique CIK-FDATE pairs. We compile the textual inputs and execute the RF Classifier algorithm in five steps.

Our first step is to obtain the relevant text in DEF 14A filings discussing the election of directors. We start by requiring a DEF 14A to mention the word "elect" or "stagger" at least once to be included in the initial sample. This step reduces the sample to 176,868 DEF 14A filings. To further identify the relevant text related to the election of directors, we use regular expressions to locate 150 words immediately following variations of the section heading "Proposal 1. Election of Directors", which precedes the paragraph discussing how many directors are up for election and indicates whether there are more than one class of directors. Appendix A presents an example of a proxy statement with the accompanying text under "Proposal No. 1 Election of Directors". We identify these paragraphs for 85.3% of the DEF 14A filings using this approach.

Because we cannot capture all potential variants of "election of directors" mentioned in the DEF 14As, our second step is to conduct two specific keyword searches that would indicate the presence of a classified board. We search the DEF 14A filings for variations of the word "class" and "term" and keep the ten words before and after each instance. We require the word "director" or "board" to appear within these ten words to be considered a valid keyword match. For "class", this restriction is intended to remove instances where "class" refers to share classes. For "term", we also require the phrase "[number] [optional non-word character] year" or "stagger" to appear within these ten words. This criterion is designed to capture instances when a firm mentions directors having "three-year terms" and other variations of this phrasing. We identify at least one of these keywords for 66.0% of the sample. These keywords are found in 59.1% of the sample that we could not identify the election of directors-paragraphs described earlier. We combine all the paragraphs and texts into one corpus for each CIK-FDATE pair.

Third, we clean the data for apparent errors, obtain each firm's GVKEY and PERMNO identifiers, and drop firms with a two-digit standard industrial classification (SIC) code of 67 ("Holding & Other Investment Offices"), resulting in 110,511 remaining firm-year observations.

The fourth step is to remove stop words (except "i") and numbers unrelated to classified boards (e.g., years 1940-2020 and ages 20-99) from the text and reduce each word to its stem using the Porter stemmer technique. We convert this text into unigrams and bigrams (one- and two-word phrases) that indicate whether the specific phrase appears at least once and include only phrases that appear in at least 1,000 of the filings, resulting in a corpus of 2,287 phrases that we use as inputs into the RF Classifier algorithm. We merge the text with the classified board data from ISS, resulting in 39,998 DEF 14A filings that match to ISS. Among these observations, we use 80% of them as our training sample and the remaining 20% as the out-of-sample test dataset.

Our final step is to determine the RF Classifier model parameters and make the out-of-sample predictions using the 20% reserved test sample. To obtain model parameters, we run a short simulation to optimize the model for in-sample performance that considers as key parameters (i) the number of trees in the forest (number of estimators), (ii) the maximum number of levels in each tree (maximum depth), (iii) the minimum number of samples to split a node (minimum sample split), (iv) the minimum number of samples at each leaf node (minimum sample leaf), and (v) the maximum number of predictors to use for each individual tree. The RF Classifier algorithm cycles through several combinations of the parameter values and determines the best parameters given the best accuracy using cross-validation techniques in the training sample. We use the "best RF" to predict the classified board status for the out-of-sample test dataset and evaluate the algorithm's success. We then extend the predictions to the universe of firms with DEF 14A filings.

One of the unique features of the RF Classifier is that the algorithm provides which variables have the most predictive power. To calculate the variable importance of each predictor *i*, RF Classifier runs through the same tree but gives a random split on each node in the forests related to predictor *i*. At the end of each run, the importance of each predictor is measured as the difference in prediction performance when the specific predictor is permuted randomly so that its influence is omitted. Figure 1A tabulates the 25 phrases with the highest predictive power in determining a firm's classified board status. These 25 phrases account for 37.6% of the variable importance among the 2,287 phrases, with the top three accounting for 9.6%. Intuitively, given that classified boards are typically divided into three classes, with each class serving three-year terms, the top three phrases based on the stemmed words are "three year", "three class", and "divid".

A potential concern with extending our predictions to firms outside the ISS database is that the text describing the election of directors could differ between the S&P 1500 firms that ISS collects data on and the non-S&P 1500 firms that it does not. This possibility creates problems because our out-of-sample test validation is based on S&P 1500 firms, which could result in underestimating the propensity for non-S&P 1500 firms to (not) have a classified board if there are systematic differences in how these firms disclose their election process. To mitigate this concern, we perform several validity checks. First, we compare the overlap in word usage in describing the election of directors for S&P and non-S&P 1500 firms. Figure 1B shows that the fraction of S&P 1500 and non-S&P 1500 firms mentioning the 25 most important phrases, as measured by their variable importance, is very similar. As a second check, we calculate a cosine similarity value of 0.993 between the fraction of S&P and non-S&P 1500 firms using each of the 2,287 phrases, indicating that both groups use nearly identical wording.[4]

2.2.3. Validating our classified board predictions and manually inspecting the dataset

Given that our application of the RF Classifier is a new approach to predicting a classified board, validating our measure and assessing the out-of-sample prediction accuracy is important. We use three different approaches to assess the validity of our predictions, which we summarize in this section and provide details of in the Internet Appendix. First, we test the accuracy rate. As expected, the in-sample prediction accuracy is extremely high, at almost 99.9%. Our out-of-sample prediction accuracy is also very high at 97.3% (with 1.5% false negatives, where our classification

[4] As mentioned previously, ISS collected data in 2017 for every firm in the Russell 3000. Thus, as a third validity check, we calculate the out-of-sample error rate for the non-S&P 1500 firms in 2017. There are 1,118 non-S&P 1500 firms in 2017, but only 228 are in the test sample. We find only eight differences among these 228 observations.

algorithm assigns a firm as not having a classified board but ISS does, and 1.2% false positives, where the algorithm assigns a firm as having a classified board but ISS does not).

Second, to further illustrate the power of the RF Classifier, we compare our approach to a traditional keyword search method (e.g., Karakaş and Mohseni, 2021). If we consider the keyword searches around "class" and "term" as described in the prior section and assign a classified board to any firm with these keywords, the error rate is 22.2% (21.3% false positives and 1.0% false negatives). If we refine this classification by requiring the word "class" be followed by "i", "ii", "iii", "1", "2", or "3" or preceded by "two" or "three", the error rate decreases to 8.7% (6.7% false positives and 2.0% false negatives). Modifying the keyword search this way highlights the approach's shortcomings: making the search stricter to reduce false positives increases the false negatives. Moreover, the predictions quickly lose parsimony and become much more ad hoc and less generalizable as a method. Conversely, the RF Classifier has the advantage of needing fewer restrictive refinements and producing a lower error rate than the keyword search method. Specifically, using the same text around these keywords, the RF Classifier produces a total sample error rate of 1.6%, an 81.0% (=1.64/8.68-1) improvement over the refined keyword search.

Lastly, we manually check all instances when our predictions do not match those in the ISS database and when any firm in our sample changes its classified board status. Discrepancies between our predictions and ISS arise from a few main sources. One source is that firms occasionally file the wrong document, such as a DEFM 14A related to a merger rather than the annual proxy statement. A second source is that firms sometimes file a proxy statement proposing to adopt or disband a classified board, but the proposal fails. Differences also arise in a few circumstances due to the imperfect matching of firms across the databases.

The final source of discrepancy is inconsistent coding when distinguishing between when firms vote to (de)classify the board and when the (de)classification is fully implemented, which is also an issue in the ISS data. Firms typically phase in board declassification over the few years after the proposal is approved, and these differences in the timing have implications for different analyses. For example, when examining the determinants of the decision to declassify, the relevant date is when shareholders pass the resolution, not when the board is fully declassified. In contrast, when examining the relation between firm outcomes, such as M&A decisions, the relevant period is when all directors can be replaced at the annual meeting (i.e., full implementation) because this creates the disciplining incentives. Consequently, we create two classified board indicator variables that distinguish between when firms vote to approve to (de)classify their board and when board (de)classification is fully implemented. We use the voting date for all our analyses.

2.3. Collecting classified board data for pre-EDGAR filings and IPO years

To obtain classified board data before electronic filings were available on EDGAR, we hand-collect data from microfiche (available from the University of Tennessee's library) beginning in 1991. For all firms, we determine the first year when a firm shows up in the Compustat database, and the earliest year we have its electronic filings. If a firm does not have electronic filings, we determine the last year when it has data in Compustat. We match company names to the microfiche proxy statements. We then use the microfiche scanner to determine whether the firm had a classified board in the first year they entered the sample beginning in 1991 and the last year the firm has data available in Compustat (unless we already have this data from the electronic filings). If a firm's classified board status is the same in these first and last years, we assume the intermediate years have the same status. If a firm's classified board status changes between the first and last year, we search all intermediate years to determine when its status changed. In total, we hand-collect classified board data for an additional 7,614 firms before EDGAR filings were available, increasing the sample size by an additional 22,892 firm-year observations.

When a firm has its IPO, it does not file a DEF 14A until next year's annual election. Therefore, we hand-collect classified board information from each firm's last IPO filing (S-1 or S-1/A) before the IPO date to obtain information on a firm's classified board status for its IPO year. When we cannot find an IPO prospectus for a firm, such as in the pre-EDGAR years, we read the first DEF 14A filing after its IPO to determine whether it had a classified board at the time of the IPO. If the first DEF 14A proposes to declassify the firm's board, we know it had a classified board at its IPO. Similarly, if the first DEF 14A proposes to adopt a classified board, we know the firm did not have one at its IPO. If no changes are proposed in the first DEF 14A and the entire board of directors are not up for reelection, then we know the firm had a classified board at its IPO and in its first year. Similarly, if no changes are proposed in the first DEF 14A and all directors are up for reelection, then we know the firm did not have a classified board at its IPO and in the first year. By reading through the first DEF 14A and given that firms rarely change their classified board status over their first year as a public firm based on the data for which we have IPO prospectuses, we have a high degree of confidence in coding IPO years using this approach.[5]

2.4. Sample overview

While we determine the classified board status of all firms with DEF 14A filings, we impose the following requirements for firms to be included in our analyses: (i) the firm can be matched to CRSP, (ii) the firm has valid information for its book value of assets, (iii) firm age is non-negative, and (iv) the firm's SIC code is less than 9100 (i.e., its industry classification is not public administration and is classifiable). These restrictions yield a sample of 136,094 firm-year observations. Appendix B provides definitions for the main variables used in our analyses.

Table 1 compares key firm characteristics for firms with and without classified boards (i.e., unitary boards). For this table and later regressions, we require all firm-level variables to be non-missing, and we winsorize continuous variables at the 1st and 99th percentiles. Almost all characteristics are statistically different between the samples. Over the entire sample period, firms with classified boards tend to be larger (based on medians and log assets), have more institutional ownership, be incorporated in Delaware, and be younger. However, as we discuss in later sections, several of the differences between the two groups change over time.

3. Trends in Classified Boards

3.1. Trends in use of classified boards by time and firm age

In Figures 2A-2C, we examine the trends in firms' use of classified boards over time and by firm age. In this and subsequent figures, we tabulate results (i) without any controls, (ii) that control

[5] As an additional check, we compare our data for IPO years to the data collected and kindly shared by Johnson, Karpoff, and Yi (2022). Out of the 1,996 overlapping observations, only 14 (0.7%) are coded differently.

for the same firm characteristics used by Johnson, Karpoff, and Yi (2022), which include (beginning of year) firm size, institutional ownership, whether the firm is incorporated in Delaware, whether the firm is in the S&P 1500 Index, and two-digit SIC industry fixed effects, and (iii) that include these firm-level controls and firm fixed effects.

In Figure 2A, we plot the fraction of firms with a classified board over time, showing that firms have become less likely to use classified boards during the past two decades. Based on the results without controls, 41.2% of firms had a classified board in 1991-92, and this percentage increased through the 1990s and early 2000s before reaching a peak of 55.5% in 2003-04. However, from this point forward, the fraction of firms with a classified board began to decline significantly to 43.8% in 2019-20. Including firm-level controls and industry fixed effects has little effect on the overall trend beyond increasing the steepness of the decline in the use of classified boards. For example, in the model that controls for industry fixed effects, roughly 55% of firms had a classified board in the early 2000s, and this value dropped to 38.9% in 2019-20. Adding firm fixed effects magnifies this trend further, showing that the fraction of firms with a classified board dropped from about 54% in the early 1990s to 29.5% in 2019-20.

These initial findings suggest that, in general, firms have been progressively less likely to use classified boards since the mid-2000s, consistent with the claim made by a number of leading legal experts that "slowly but surely, corporate America is giving up the [classified] board" (Subramanian, 2007) and that "[classified boards] are becoming rare and are on their way toward endangered-species status" (Strine, 2014). However, prior to our study, most extant evidence of a declining trend in classified boards comes solely from S&P 1500 firms in the ISS database (e.g., Ganor, 2008; Cremers, Litov, and Sepe, 2017). In Figure 2B, we utilize our new dataset and the model without controls to examine whether this claim holds for firms outside of the S&P 1500. The figure starts in 1995-96 with the creation of the S&P 1500 Index and decomposes the trends in classified board usage between firms in the S&P 500, 400, and 600, and non-S&P 1500 firms.

We find that while the use of classified boards has been declining substantially among firms in the S&P 1500, especially those in the S&P 500, the trend in classified board usage has been generally increasing for the non-S&P 1500 firms. To illustrate this difference, the percentage of

S&P 500 firms with a classified board dropped from 59.9% in 1995-96 to only 12.2% in 2019-20, whereas about 42.4% of non-S&P 1500 firms had a classified board in 1995-96 and 51.7% had this provision in 2019-20.[6] Thus, while classified boards have become rarer among S&P 1500 firms, they remain a common defense for firms outside of the Index.

In Figure 2C, we explore differences in firms' use of classified boards as they progress through different stages of their life cycle. We decompose firm age into seven groups based on the number of years since a firm's IPO: ages 0-1, 2-3, 4-5, 6-7, 8-10, 11-15, and ≥16. Consistent with prior work, the figure shows that firms near their IPO date commonly use classified boards (e.g., Field and Karpoff, 2002; Johnson, Karpoff, Yi, 2015; Field and Lowry, 2022), whereas this fraction steadily declines as firms mature. Based on the results without controls, 57.4% of firms aged 0-1 use classified boards, but this fraction declines to 47.9% by the time they reach ages 8-10 and to 43.6% for mature firms aged ≥16. This life cycle pattern showing that as firms mature, they are less likely to use classified boards is consistent with economic analysis that suggests that the benefits associated with classified boards is greatest among younger firms, whereas the costs become more pronounced as firms reach their mature stages (Johnson, Karpoff, and Yi, 2022).

3.2. Trends in use of classified boards over time by firm age

In Figures 2D-2F, we examine whether classified board usage at different stages of a firm' life cycle has changed during the past three decades by plotting the fraction of firms with a classified board over time by four firm age groups: ages 0-2, 3-6, 7-10, and ≥11. Based on the model without controls and consistent with Field and Lowry (2022), Figure 2D shows that the fraction of the youngest firms with a classified board has been increasing since the 1990s, from a low of 35.7% in 1991-92 to a high of 74.0% in 2015-16 and staying at 72.4% in 2019-20. This trend is similar for firms aged 3-6 and 7-10 during the 1990s, but the trend mostly plateaus beginning in the early to mid-2000s. For the most mature firms aged ≥11, a much smaller fraction of firms maintained

[6] The significant drop in classified board usage among S&P 500 firms from 2011-14 is consistent with reports from the Shareholder Rights Project that it successfully pushed for board declassification of these firms during this period.

classified boards over time. For firms that have been publicly traded for more than ten years, 51.3% had a classified board in 1991-92, and this fraction dropped to 33.5% in 2019-20.

Including firm-level controls and industry fixed effects in Figure 2E does not change the patterns much, whereas Figure 2F, which includes firm fixed effects, shows a much smoother trend over time. The youngest firms aged 0-2 exhibit a flat to slightly increasing likelihood of having a classified board over our sample period. For firms aged 3-6, there has been a slight decrease in the use of classified boards over time, whereas the sharpest declines are observed among more mature firms aged 7-10 and ≥11. For instance, throughout the 1990s, the most mature firms aged ≥11 maintained classified boards at a steady rate of around 53%, but this fraction began to decline starting in the early 2000s, reaching a low of 24.6% in 2019-20.

3.3. Trends in use of classified boards by firm age, decade, and IPO cohort

In Figure 3, we present our key analysis by using our new dataset to investigate whether, during the past 30 years, firms have used classified boards differently over their life cycle depending on their decade or IPO cohort. Figures 3A-3C examine whether the life cycle patterns in classified board usage from Figure 2 have changed over the past 30 years by plotting the fraction of firms with a classified board by seven firm age groups and across three separate decades: 1991-2000, 2001-10, and 2011-20. Figure 3A shows that in analyses without controls, the use of classified boards only slightly declines as firms age from years 0-15 during the 1991-2000 decade, before increasing for the most mature firms aged ≥16. This result is consistent with less attention being paid to classified boards and firms having fewer incentives to declassify their boards as they age during this period. However, beginning in the 2000s, and especially after 2010, there is a steep decline in the use of classified boards as firms age. For the 2011-20 decade, 73.4% of firms aged 0-1 had a classified board, and this fraction decreased to 33.0% for firms aged ≥16.

Figure 3B shows that the patterns are similar when controlling for firm-level characteristics and industry fixed effects but with a much smaller increase for the most mature firms during the 1991-2000 decade. However, Figure 3C, which controls for firm fixed effects, shows there is an increase in classified board usage as firms aged during the 1991-2000 decade. Conversely, during the 2000-10 decade, 59.7% of firms aged 0-1 had a classified board, and this fraction dropped to 47.7% for firms aged ≥16. The decline is even more pronounced during the 2011-20 decade, with 56.7% and 39.6% of the youngest and most mature firms having a classified board, respectively.

In Figures 3D-3F, we plot the fraction of firms with a classified board across a firm's life cycle conditional on its IPO cohort. We break firms into four groups based on their IPO year: ≤1990, 1991-2000, 2001-10, and 2011-20. Focusing on the models without controls, there are two key takeaways from Figure D. First, the fraction of firms aged 0-1 with a classified board is sequentially higher across each decade, with values of 30.2%, 51.4%, 63.9%, and 73.7% for firms with IPOs during the ≤1990, 1991-2000, 2001-10, and 2011-20 periods, respectively. Second, during the earliest (last) two decades, firms declassify their boards slower (faster) as they mature. By age 8-10, 39.2% and 53.9% of firms with an IPO between ≤1990 and 1991-2000, respectively, still had a classified board, while the values drop to 50.9% and 48.0% for firms with IPOs between 2000-10 and 2011-20, respectively. Adding controls and industry fixed effects makes the fraction of firms aged 0-1 with classified boards more similar across the decades, suggesting that part of the rise in the fraction of young firms with classified boards is driven by sample composition. However, the figures continue to show steeper declines in the use of classified boards over a firm's life cycle across the more recent IPO cohorts. While including firm fixed effects mutes the declines across the decades, Figure 3F still shows that relative to firms with IPOs before 2001, those with IPOs during the last two decades declassified at faster rates (i.e., at an earlier age).[7]

While Figure 3 plots the fraction of firms with a classified board for all age groups by decade and IPO cohorts, it does not show whether the changes in classified board usage by these cohorts are statistically significant. Therefore, using the models with controls and firm fixed effects, Table 2 examines whether firms adjust their classified boards over their life cycle relative to the youngest firms aged 0-1 (i.e., the base reference group) significantly different by decade and IPO cohort. Column 1 includes all firms over the full sample, columns 2-4 separate firms by decade, and

[7] Due to our dataset beginning in 1991, we do not have complete information on classified boards for firms with IPOs before 1990. Thus, because our data on the classified board status of IPO firms before 1990 is incomplete, we interpret the trends (and estimates from later analyses) in the use of classified board for this IPO cohort with caution.

columns 5-8 group firms by IPO cohort. Focusing on the life cycle effect over the full sample, column 1 shows that firms make minimal changes in their use of classified boards until they are aged ≥11. Specifically, although the coefficients on the 2-3, 4-5, and 6-7 age dummies are positive and statistically significant, the economic magnitudes are small at less than one percentage point. Conversely, the coefficients on the 11-15 and ≥16 age dummies are -2.4% and -7.9%, respectively, and statistically significant, indicating that mature firms are less likely to have classified boards.

Columns 2-8 confirm that decade and IPO cohort effects significantly change the way firms use classified boards over their life cycles. Consistent with Figures 3C and 3F, columns 2 and 5 show that during the 1990s or for firms with an IPO prior to 1991, these firms do not declassify as they age. Rather, relative to firms' IPO years, the likelihood of having a classified board increases significantly as they mature. In contrast, columns 4 and 8 show that during the most recent decade or for firms with IPOs after 2010, the likelihood of having a classified board quickly declines as firms age. Comparing the results across columns also reveals dramatic differences in coefficients for the same age groups, indicating decade and IPO cohort-specific age effects. For example, coefficients on the age group 2-3 decline monotonically from the earliest to latest decade and IPO cohort, switching from significantly positive to significantly negative.

Taken together, the findings in Figure 3 and Table 2 show that life cycle patterns in classified board usage have changed over the past 30 years. Firms that aged or had an IPO during the earliest decade in our sample were the most likely to maintain their classified boards throughout their life cycle, consistent with this takeover defense being sticky and rarely removed by firms over this period (e.g., Cremers and Ferrell, 2014). Conversely, firms that aged and went public during the more recent decades have been increasingly likely and quicker to declassify their boards as they mature, as recent economic theory predicts is value-maximizing (Johnson, Karpoff, and Yi, 2022).

3.4. Trends in board declassification by firm age, decade, and IPO cohort

In Figure 4, we analyze the trends in the rate that firms declassify their boards over their life cycle by decade and IPO cohort. For this analysis, we limit the sample to firms that had a classified board in year t-1. The dependent variable, *Declass*, is an indicator that equals one if a firm had a classified board in year *t*-1 but no longer has this provision in year *t*, and equal to zero if a firm has a classified board in years *t*-1 and *t*. We show results using models without controls, and with firm-level controls and either industry or firm fixed effects.

In Figures 4A-4C, we examine life cycle effects on the rate of board declassification by decade. Based on the model without controls, Figure 4A shows that, across age groups, the rate that firms declassified their boards during the 1991-2000 decade remained flat at around 0.6% to 1.1% per year. Conversely, during the 2000-10 decade, board declassification rates rose as firms aged. For firms aged 0-1, only 0.7% declassified their boards, but this rate increased to 3.3% for firms aged ≥16. In the 2010-20 decade, the rate of board declassification is generally higher for all firms aged ≥2 when compared to firms in similar age groups during the prior decade. For firms aged 0-1, only 0.1% of firms declassified their boards, but this rate increases to 3.5% for firms aged ≥16. Controlling for firm characteristics and industry fixed effects does not affect the pattern much. However, after controlling for firm fixed effects, Figure 4C shows that the likelihood that a firm declassifies its board increases as firms age across all three decades. Although, for the 1991-2000 decade, the increase is less steep when compared to the following two decades.

In Figures 4D-4F, we examine life cycle effects on board declassification rates by IPO cohort. In models without controls, Figure 4D shows that firms with IPOs before 2000 had higher declassification rates than those with IPOs between 2001 and 2020. However, these two latter cohorts declassify their boards at relatively faster rates from ages 2-5. Firms aged 6-10 and going public during 2001-10 continue to declassify at a faster rate than similarly aged firms with IPOs from 1991 to 2000, while the declassification rates of firms going public in the most recent decade slow more at these ages than any other cohort. Controlling for firm characteristics and industry fixed effects does not affect the results. After including firm fixed effects, Figure 4F shows that declassification rates have increased over a firm's life cycle across the IPO cohorts, with the rates being generally faster among all age groups of firms going public during the last two decades.[8]

[8] For completeness, Internet Appendix Figure IA.2.1 conducts the same analysis as Figure 4 but for classified board adoption rates. Overall, the general trends in the fraction of firms adopting a classified board are similar for each decade and IPO cohort, decreasing over time and over a firm's life cycle.

4. What Explains the Trends in Classified Board Usage?

We next examine potential drivers of the classified board trends. Our main hypothesis is that changes to the U.S. corporate governance system, including stronger shareholder rights protection and more concentrated institutional investor ownership has intensified the pressure on firms to adjust their classified boards more optimally over their life cycle. We also explore whether changes in the nature of firms or the market for corporate control over time could explain these trends.

4.1. Changing nature of firms

Over the last 30 years, there have been several changes in the composition of public firms. For instance, nowadays, there are fewer public firms, firms are on average larger, and they increasingly rely on intangible assets (e.g., Doidge, Karolyi, and Stulz, 2017; Kahle and Stulz, 2017). Thus, it could be that underlying changes in endogenous firm characteristics over time drive the time-varying decade and IPO cohort effects we find in classified board usage over the life cycle.

To assess whether the changing nature of firms can explain our main results, we revisit our findings in Figure 3. The figure indicates that trends in classified boards are largely unrelated to common firm-specific factors that likely influence a firm's takeover defense policy (e.g., firm size, state of incorporation). These results also hold after controlling for firm fixed effects, which account for the possibility that the patterns are driven by changes in the composition of firms in our sample because the trends are obtained from exploiting only within-firm variation.

In Figure IA.2.2, we further add to this evidence by analyzing whether these patterns hold after controlling for a more robust set of firm characteristics. Specifically, the figure shows that the patterns from Figure 3 continue to hold after further controlling for firm size squared and cubed, Tobin's Q, operating income scaled by book assets, book leverage, capital and R&D expenditures scaled by book assets, stock return volatility, and the natural logarithms of share turnover and analyst coverage. Overall, differences in trends in classified board usage over a firm's life cycle are unchanged after including this extensive set of controls in regressions with industry and firm fixed effects, suggesting that changes in firm composition do not drive the trends.

4.2. Changes in M&A activity

Another possible explanation for the difference in the use of classified boards over a firm's life cycle across decade and IPO cohorts relates to differences in M&A trends. For example, if compared to the 1990s, mature firms are less likely to be targeted for acquisition during the last two decades, then their need for a classified board as a takeover defense would have decreased during this period. Thus, firms in the later years of our sample might declassify their boards sooner as they mature because they no longer need this defense for takeover protection.

We investigate this explanation in Figure IA.2.3 by examining the likelihood that firms are targeted for a takeover as they mature by decade and IPO cohort. In general, the figures show that the likelihood of a firm being taken over increases from its IPO year to a few years after and then decreases. However, after controlling for firm fixed effects, takeover likelihood steadily increases as firms age. Moreover, while takeover activity has generally changed over time, these changes appear for all age groups. Thus, changes in the market for corporate control cannot explain the different life cycle effects on classified board usage we observe across decades and IPO cohorts.

4.3. Changing attention, visibility, and scrutiny on corporate governance

We next investigate whether increasing attention, visibility, and scrutiny on corporate governance practices over the past 30 years contributed to the decade and IPO cohort effects we document in classified board usage over a firm's life cycle. In more recent decades, firms have been more intensely covered by the media, analysts, and academics and have more concentrated institutional ownership. This public scrutiny and shareholder pressure may have influenced firms to declassify faster over time (e.g., Bebchuk, Cohen, and Wang, 2013; Appel, Gormley, and Keim, 2016). Indeed, boards often explicitly discuss the increased pressure and concerns from investors regarding board classification. For example, Skyworks Solutions' 2011 proxy statement says:

> "*The Board of Directors recognizes that a classified structure may offer several advantages, such as promoting board continuity and stability, encouraging directors to take a long-term perspective, and ensuring that a majority of the board will always have prior experience with the Company... However, the Board of Directors also recognizes that a classified structure may appear to reduce directors' accountability to stockholders, since such a structure does not enable stockholders to express a view on each director's performance by means of an annual vote. Moreover, many institutional investors believe*

that the election of directors is the primary means for stockholders to influence corporate governance policies and to hold management accountable for implementing those policies."

4.3.1. Rise of attention from the news media and academics

First, we examine how attention from the news media and academics on corporate governance and classified boards has changed over time and whether it is consistent with the trends in board declassification. The corporate accounting scandals in the early 2000s damaged investor confidence and brought to light a widespread lack of internal controls and effective governance structures in U.S. firms. In 2002, the U.S. Congress passed the Sarbanes-Oxley (SOX) Act to protect investors from fraudulent financial reporting. These scandals and the corresponding regulatory response received substantial news coverage. Figure 5A shows this spike in news media attention. Before 2001, the Wall Street Journal (WSJ) published fewer than 200 articles each year covering topics related to corporate scandals, fraud, and misconduct. Coverage of these topics sharply increased in 2002 to over 1,000 articles, clearly reflecting heightened attention to governance. After peaking in 2002, WSJ coverage of these topics gradually declined, returning to its pre-SOX level by 2010 and remaining at fewer than 200 articles per year since.

Along with the heightened attention to corporate scandals, the news media also started paying more attention to corporate governance and shareholder activism. Figure 5A also shows that the number of WSJ articles mentioning corporate governance and shareholder activism increased from less than 20 in the late 1990s to 80 in 2002. Moreover, unlike the coverage of corporate scandals, the media's attention to governance and activism remained relatively stable through 2020.

Figure 5B further shows a rise in academic attention to classified boards. The number of Google Scholar articles that mention classified boards has increased over tenfold from only 42 in 1996 to 463 in 2020. Requiring each article's title to mention classified boards reduces the number of articles, but there is still an upward trend in academic attention on classified boards, averaging less than one article per year in the first five years of the sample to almost seven per year in the last five years. Finally, conducting a similar analysis for articles posted on the Social Sciences Research Network (SSRN), we count how many articles mention classified boards in the title, abstract, or keywords. Like the Google Scholar results, the number of SSRN articles averaged one per year in the first five years and almost nine articles per year in the last five years. Overall, we document a steady rise in media attention to corporate governance issues and academic attention to classified boards, consistent with Bebchuk, Cohen, and Wang (2013).

4.3.2. Rise of attention from investors

Another important trend likely associated with increased shareholder pressure toward board declassification is the rise in institutional ownership, whose fund managers have a large incentive to call for governance changes that would increase firm value (e.g., Lewellen and Lewellen, 2022). For instance, after the Enron and WorldCom scandals, Patrick McGurn (special counsel to ISS) commented that, in its proxy voting advisory role to institutional investors, "ISS often receives inquiries as to [its] views on the two or three governance changes that…would help investors to avoid similar market meltdowns in the future," and that, "unquestionably, the item on [its] wish list…is the call for annual elections of all members of corporate boards" (McGurn, 2002).

Especially important in this context is the rise of index funds. Index funds are passive owners that hold a certain amount of a firm's shares in accordance with their benchmark weights. In general, investors can exert influence when they do not agree with a firm's governance structures by selling shares (i.e., "The Wallstreet Walk"), actively engaging with managers in private communications, or filing shareholder proposals (e.g., Shleifer and Vishny, 1986; McCahery, Sautner, and Starks, 2016). By the nature of their charter and the need to reduce tracking error, index funds are mostly barred from the first approach and must engage with firms if they are displeased with specific policies (e.g., Boone and White, 2015; Appel, Gormley, and Keim, 2016; Crane, Michenaud, and Weston, 2016; Azar, Schmalz, and Tecu, 2018).[9]

To get a sense of how institutional ownership has changed over time, Figure 6A plots the average amount of shares owned by 13-F institutional investors between 1991 and 2020. Figure 6B is similar, except that we limit institutional investors to quasi-indexers using the classifications

[9] However, some disagreement arises in recent literature on the monitoring role of index investors (e.g., Schmidt and Fahlenbrach, 2017; Hirst and Bebchuk, 2019; Heath, Macciocchi, Michaely, and Ringgenberg, 2022).

from Bushee and Noe (2000) and Bushee (2001). Figure 6C plots the average fraction of shares owned by the Big Three index fund managers (i.e., Blackrock, State Street, and Vanguard).

Figure 6 shows an increase in institutional ownership over time. Focusing on the model without controls, Figure 6A shows that total institutional ownership was 28.2% in 1991-92 and rose to 62.2% in 2020. Figure 6B shows that quasi-indexer ownership was 14.3% in 1991-92 (and only 13.1% in 2001-02) and increased to 38.9% in 2007-08. This rise in index fund ownership corresponds to when firms began to decrease their use of classified boards substantially and is consistent with the view that more concentrated ownership by index funds likely increased shareholder engagement with managers on governance issues over this period. Lastly, Figure 6C shows the substantial growth of Big Three ownership. Big Three ownership of shares was small in 1991-92, but it rapidly increased to 3.8% in 2007-08 and to 14.2% by 2020. Importantly for our later analysis of voting on proposals to declassify, while many shareholders do not vote, the Big Three tend to vote all their shares (e.g., Hirst and Bebchuk, 2019; Griffin, 2020).

Overall, large rises in attention among the news media and academics and increased ownership concentration by institutional investors are consistent with our hypothesis that firms' governance policies have become more intensely scrutinized over time, and that this in part has led to the increased pressure on firms to declassify their boards. We next examine whether this pressure and shift in sentiment against classified boards ultimately culminates in an increase in and support for shareholder proposals demanding board declassification.

4.3.3. Shareholder proposals to declassify boards

Shareholder pressure via activism plays a leading role in moving firms away from classified boards. In particular, activism in the form of shareholder proposals is one of the most important mechanisms investors use to push firms to declassify (e.g., Karpoff, Malatesta, and Walkling, 1996; Thomas and Cotter, 2007; Guo, Kruse, and Nohel, 2008). Motivated by this work, we analyze proposals to declassify using voting outcome data from Voting Analytics, which is available from 2003 to 2020. Thus, we focus on proposals that are eventually added to the annual proxy. While this approach could understate the true number of proposals being put forth by shareholders because managers can block proposals from being voted on at the annual meeting, it is likely not a major concern for proposals on board declassification (Ising, 2012).

Firms can respond to shareholder proposals by (i) attempting to exclude them under SEC Rule 14a-8, which allows firms to exclude a proposal that deals with matters related to the firm's ordinary business operations, (ii) including the proposal on the proxy statement with the firm's vote recommendation, or (iii) implementing the proposal by seeking shareholder approval. In cases (ii) and (iii), Voting Analytics would capture these proposals. Case (i) could be a concern, but for proposals related to classified boards, the SEC has historically deemed these proposals as not excludable under the rule because they are not viewed as part of the firm's ordinary business operations (Ising, 2012). Thus, examining the prevalence of proposals related to classified boards that make it to the proxy statement should be a reasonable proxy for the total number of proposals.

Figure 7A shows that the fraction of firms with a classified board in either year *t* or *t*-1 that vote on proposals to declassify their boards has increased over time. Based on the models without controls, from 2003-04 to the peak rate in 2013-14, the fraction of firms voting to declassify almost tripled from 2.2% to 6.1%, which corresponds to the large drop in the fraction of firms with a classified board shown in the previous figures. This fraction dropped to 3.3% in 2015-16 but steadily rose to 4.6% by 2019-20. This finding suggests that investors put more effort into monitoring management and are more actively engaged in proposing changes to influence governance over time. Controlling for firm-level characteristics and industry fixed effects has little effect on this trend, while controlling for firm fixed effects makes the trend even more pronounced.

Figures 7B and 7C examine trends in shareholder support in terms of voting outcomes to better understand how shareholder sentiment towards board declassification has changed over time. Figure 7B plots the average percentage of votes cast in favor of declassifying a board. Further, because voting percentages include votes by external investors and insiders, Figure 7C focuses on votes cast specifically by investors by plotting the average fraction of mutual funds that vote to declassify a board. In these figures, we do not include results from regressions with firm fixed effects because firms rarely vote on declassification more than once. Overall, there is a steady increase in the average voting support of proposals to declassify. Based on the models without controls, Figure 7B shows that 75.7% of votes were cast in favor of declassifying in 2003-04, whereas this fraction increased to 95.9% in 2019-20. Figure 7C also shows that the fraction of mutual funds supporting declassification increased from 92.0% in 2003-04 to 98.4% by 2019-20.

The findings in Figure 7 suggest that shareholders have become more active in proposing changes to board structures, and when they do take such actions, they succeed with more support. Collectively, the results in Sections 4.3.1-4.3.3 are consistent with increases in attention and scrutiny on corporate governance policies and more concentrated institutional ownership, culminating in more concerted shareholder pressure on firms to declassify (e.g., Belinfanti, 2008; Dyck, Volchkova, Zingales, 2008; Appel, Gormley, and Keim, 2016; McCahery, Sautner, and Starks, 2016; Abramova, Core, and Sutherland, 2020).

4.3.4. Change in sentiment toward classified boards

Given our findings that institutional ownership has steadily increased over time, we investigate whether changes in institutional owners' and especially index funds' attitudes toward classified boards play a role in explaining the trends. To do so, we first regress our classified board indicator on total institutional ownership interacted with 5-year interval dummy variables across four age groups: ages 0-2, 3-6, 7-10, and ≥11. In these analyses, we only tabulate results that include firm-level controls and firm fixed effects to examine how the relation between having a classified board and institutional ownership changes over time within the same firm. Columns 1-4 of Table 3 tabulates the coefficients on these interaction terms. Overall, for the youngest firms, the relation between having a classified board and institutional ownership is relatively flat from 1991 to 2020, with coefficients never being statistically different than zero. However, for the most mature firms aged ≥11, the coefficients on institutional ownership are positive and significant during the 1990s. This sentiment becomes more neutral in the mid-2000s and turns significantly negative after 2010.

Second, we regress our classified board indicator on quasi-indexer and non-quasi-indexer ownership interacted with the 5-year interval dummy variables. Columns 5-8 also show no changes in the relation between having a classified board and quasi-indexer ownership over time for younger firms. However, for the most mature firms, during the 1990s, the results show positive and statistically significant coefficients on the quasi-indexer ownership interaction terms. This sentiment becomes more neutral in the mid-2000s and turns significantly negative after 2010. Last, columns 9-12 are similar, except we regress the classified board indicator on Big Three and non-Big Three ownership interacted with the 5-year interval dummies. Compared to quasi-indexers, the change in sentiment towards having a classified board among the Big Three is even more drastic for mature firms, turning negative and statistically significant after 2005, which is consistent with the observation that all three of these fund managers have policies to generally vote in favor of board declassification (Bebchuk, Hirst, and Rhee, 2013). Overall, the results suggest that institutional ownership, especially by quasi-indexers and the Big Three, has risen over time, particularly in the latter half of the sample, and that ownership by these investors during this period of increased governance scrutiny associates negatively with board classification.

4.3.5. S&P 1500 membership, firm size, and classified boards

We further assess the role of increased scrutiny of governance practices on the classified board trends by examining how being in the S&P 1500 Index and firm size affect the likelihood of having a classified board over time. Institutional ownership, especially index ownership, is greater for S&P 1500 and larger firms (e.g., Iliev, Kalodimos, and Lowry, 2021). Additionally, because the media, analysts, and academics more intensely cover S&P 1500 and larger firms, the governance practices of these firms are especially likely to be scrutinized and influenced by this scrutiny.

Like the prior analysis, we regress our classified board indicator on time dummies interacted with an S&P 1500 indicator or the natural logarithm of book value of assets (results are similar using market value of equity) across the four age groups, tabulating results that include firm-level controls and firm fixed effects. Columns 1-4 of Table 4 show that until 2010, the most mature firms in the S&P 1500 Index were significantly more likely to have classified boards than firms outside the Index. After 2010, this relation becomes significantly negative. For younger firms, there is no difference in classified board usage between Index and non-Index firms over time.

When we proxy for governance scrutiny using firm size, columns 5-8 show that except for the youngest firms, larger firms were significantly more likely to have a classified board until 2005.

After this year, this relation becomes insignificant for firms aged 3-10, and turns negative for the most mature firms aged ≥11. For the youngest firms aged 0-2 years, the relation between firm size and having a classified board has been positive but largely flat throughout the last three decades.

Figure 8 tries to establish a more causal inference by examining how the likelihood of having a classified board changes after a firm is added to the S&P 1500 Index in a stacked differences-in-differences setting. In this test, a firm joining the Index is a treatment event. We use propensity scores to match treatment firms in year *t*-1 relative to joining the Index to a set of control firms that are never in the S&P 1500.[10] We require both groups to have a classified board in the years before treatment and keep the ±3 years around the treatment year.[11] We then regress our classified board dummy on timing variables that indicate the year relative to the treatment year, firm fixed effects, and other controls. We split the sample into the three decades to examine how the effect of joining the S&P 1500 on having a classified board has changed over time. The cohort labels signify that the firm was added to the Index in one of these cohort years. For example, if a firm joined the S&P 1500 in 2012, the firm and its corresponding matched firms would be included in the 2011-2020 cohort and have sample years of 2009-2015 included in the regression.

Figure 8A (8B) plot the coefficients from these regressions without (with) firm-level controls. Both figures show statistically significant negative coefficients in the later 2011-20 decade. For this decade, in the three years after joining the Index, firms are significantly less likely to keep a classified board. In contrast, firms joining the S&P 1500 Index in the 1991-2000 and 2001-10 decades are equally likely to maintain their classified boards as the control firms.

In Figures 8C and 8D, we split the sample into firms aged <5 and ≥5 based on their age in year *t*-1. For younger firms, joining the S&P 1500 Index has little effect on having a classified board.

[10] We estimate the likelihood that a firm is in the S&P 1500 using a logit model and the covariates *Ln(Assets)*, *IO*, and *Delaware*. We then match S&P 1500 firms to non-S&P 1500 firms such that the maximum difference between their propensity scores is 0.025, they operate in the same two-digit SIC industry, and they are in the same fiscal year. We match with replacement and allow every S&P 1500 firm to be matched to two non-S&P 1500 firms.

[11] The treatment (control) group includes all firms that are (never) added to the S&P 1500 once over our sample period. For both groups, we require firms to have always had a classified board over the three years (or for all available years if data are available for less than three years) before the treatment year. Our matched sample has 685 treatment firms and 1,132 control firms.

Even in the last decade from 2011 to 2020, there is only a small and statistically significant decrease in the likelihood of having a classified board in the first year after joining the Index. In contrast, for mature firms, the likelihood of having a classified board decreased significantly after being added to the Index during the 2011-20 decade. There is no change in the likelihood of having a classified board for either age group after joining the Index during the two earlier decades.

Overall, the findings in Tables 3-4 and Figures 5-8 are consistent with the explanation that changing attitudes towards classified boards, increased scrutiny on governance, and more concentrated institutional investor ownership pressured firms to adjust their use of classified boards more dynamically over time. Nevertheless, we do not intend to claim causality because we recognize the difficulty in accurately identifying all possible factors that could contribute to these patterns, as time trends are frequently influenced by multiple factors simultaneously.

5. Trends in the Relation between Classified Boards and Firm Value

We next examine whether the life cycle effects of classified boards on firm value and the market's response to board declassification announcements has changed over the last 30 years.

5.1. Classified boards and Tobin's Q

Following Johnson, Karpoff, and Yi (2022), Table 5 examines the relation between having a classified board and Tobin's Q, separately for seven age groups: 0, 1, 2, 3-4, 5-6, 7-9, and ≥10. We control for firm size, institutional ownership, S&P 1500 Index membership, whether the firm is incorporated in Delaware, and year and two-digit SIC industry fixed effects in each regression. In Panel A, we estimate these regressions using the full sample. Consistent with the findings in Johnson, Karpoff, and Yi (2022), there is a significantly positive relation between firm value and having a classified board for newly public firms (t-stat = 2.70). However, this relation becomes significantly negative for firms aged two years and older (t-stats ranging from -3.89 to -2.24).

These findings support the claim that classified boards are valuable for newly public firms, but their costs increasingly exceed their benefits as firms mature. As hypothesized in Johnson, Karpoff, and Yi (2022), this pattern could arise from two effects. First, by insulating managers from external pressure, classified boards can promote long-term investments and bond firms to their key stakeholders (e.g., Cremers, Litov, and Sepe, 2017), which prior work shows is especially beneficial for younger firms that rely extensively on business partnerships that are subject to holdup problems arising from relationship-specific investments (e.g., Johnson, Karpoff, and Yi, 2015). Second, classified boards tend to be sticky and rarely removed by firms (e.g., Gompers, Ishii, and Metrick, 2003), even when the defense becomes costly and serves to entrench managers (e.g., Faleye, 2007). Thus, in equilibrium, if classified boards were optimally adjusted once their costs outweighed their benefits, there would be no value reversal effect over a firm's life cycle.

Our paper's key findings suggest that increases in attention and scrutiny on governance practices and more concentrated institutional investor ownership have pressured firms to adopt more optimal governance policies in the recent decades by declassifying their boards at a younger age before the defense becomes value destroying. We test this implication in Panels B-D by conducting the same value analysis as in Panel A but estimating the regressions by decade. Panel B shows that between 1991 and 2000, the relation between classified boards and firm value across age groups displays a similar reversal pattern as that in Panel A. The value reversal effect across age groups weakens in the 2000s, as shown in Panel C. Finally, Panel D shows that between 2011 and 2020, there is no longer a statistically significant relation between classified boards and firm value across the age groups, with the exception of firms aged 3-4 (t-stat = -2.00).

5.2. Announcement returns around board declassification

Next, we examine how the market responded to firms declassifying their boards over time. Following prior literature, in Figure 9, we perform a short-run stock return event study around the date of the shareholder meeting when firms vote to approve the proposal to declassify (e.g., Karpoff, Malatesta, and Walkling, 1996; Strickland, Wiles, and Zenner, 1996; Del Guercio and Hawkins, 1999; Thomas and Cotter, 2007; Cuñat, Gine, and Guadalupe, 2012). We identify 857 such meetings from 1995 to 2020. We calculate cumulative abnormal returns (CARs) over the ±1-day (Figure 9A) and ±2-days (Figure 9B) around the announcement of the successful vote to declassify. We estimate parameters used to calculate CARs using the market model with the CRSP equal-weighted index over the [-210,-11] trading days before the meeting. We regress CARs on year dummies, and estimate models without any controls, with firm-level controls, and with firm-level controls and two-digit SIC industry fixed effects. In this figure, we do not separate trends in CARs by age group due to the small sample sizes.

Focusing on the models that control for firm-level characteristics and industry fixed effects, both figures show that, on average, CARs are positive and statistically significant across the full sample period (p-value = 0.018 in Figure 9A and <0.001 in Figure 9B). Moreover, the results suggest that proposals to declassify were particularly well-received in 1999-2000, as evidenced by the significant CARs ranging from 4.4% to 8.0%. Given that most prior studies report insignificant CARs to shareholder proposals around shareholder meetings (see Denes, Karpoff, and McWilliams (2017) for a review), these positive CARs indicate that investors viewed removing a classified board around this period as enhancing corporate governance and shareholder value. The CARs remain positive after 2000 but are smaller in magnitude than in the 1999-2000 period. The smaller market response to boards declassifying over this period could reflect that the market partially anticipates firms' movement towards a more optimal takeover defense policy during the more recent decades.[12] Conversely, the CARs are not statistically different from zero before 1999.

6. Conclusion

There have been substantial changes to the corporate governance landscape over the last 30 years, including increased attention and scrutiny on governance practices and more concentrated institutional investor ownership. Our paper explores the impact of these changes on firm-level governance decision-making by examining how takeover defense usage over a firm's life cycle has evolved over this period. To do so, we build a novel dataset that tracks the use of classified boards by nearly all U.S. publicly traded firms from 1991 to 2020. With this comprehensive dataset, we investigate how firms from specific cohorts, categorized by a shared decade or IPO year, use classified boards differently as they age.

[12] Prior work also uses initial press announcements or the date when proxy materials containing shareholder proposals are mailed to measure market reactions. In unreported analyses, we use these event dates but do not find a significant market response. The insignificant results could reflect the difficulty in precisely identifying the initial date of information release and the uncertainty regarding the vote outcome.

Our results are consistent with the changes to the governance landscape increasing the likelihood and speed that firms adjust their classified boards over their life cycle. We find that, during the 1990s, classified boards were sticky and rarely removed. However, since the mid-2000s, firms that aged or went public during this period were quicker to declassify their boards as they matured, as recent economic theory predicts is value-maximizing. Additional analyses suggest that more intense scrutiny on governance and increased concentration of institutional ownership contributed to firms adjusting this takeover defense more dynamically over time. Further consistent with this explanation, we find that the relation between classified boards and firm value was positive (negative) for young (mature) firms during the 1990s and early 2000s, suggesting that firms retained their classified boards for too long. Conversely, the relation between classified board usage and value over the life cycle seems to be in equilibrium during the most recent decade, as the reversal pattern disappeared after 2010.

Overall, this paper provides novel evidence indicating that the prevailing institutional and environmental context matters for corporate governance practices. For example, our finding of decade and IPO cohort effects have several implications for researchers. In particular, it suggests that future work aiming to examine takeover defense usage over a firm's life cycle and its relation with firm value should be aware of the underlying governance landscape during the sample period being studied. These results also point to issues with not only taking a "one size fits all" approach to takeover defenses, but also with the view that "one size fits all *always*". Additionally, from a methodological perspective, we show how advances in machine learning can be used to create new comprehensive datasets, which offers many opportunities for future research.

References

Abramova, Inna, John E. Core, and Andrew Sutherland, 2020, Institutional investor attention and firm disclosure, *The Accounting Review* 95, 1-21.

Amihud, Yakov, and Stoyan Stoyanov, 2017, Do staggered boards harm shareholders?, *Journal of Financial Economics* 123, 432-439.

Appel, Ian R., Todd A. Gormley, and Donald B. Keim, 2016, Passive investors, not passive owners, *Journal of Financial Economics* 121, 111-141.

Arikan, Asli M., and René M. Stulz, 2016, Corporate acquisitions, diversification, and the firm's life cycle, *Journal of Finance* 71, 139-194.

Azar, José, Martin C. Schmalz, and Isabel Tecu, 2018, Anticompetitive effects of common ownership, *Journal of Finance* 73, 1513-1565.

Bajari, Patrick, Denis Nekipelov, Stephen P. Ryan, and Miaoyu Yang, 2015, Machine learning methods for demand estimation, *American Economic Review* 105, 481-85.

Bates, Thomas W., Ching-Hung Chang, and Jianxin Daniel Chi, 2018, Why has the value of cash increased over time?, *Journal of Financial and Quantitative Analysis* 53, 749-787.

Bebchuk, Lucian A., John C. Coates IV, and Guhan Subramanian, 2002, The powerful antitakeover force of staggered boards: Further findings and a reply to symposium participants, *Stanford Law Review* 55, 885-917.

Bebchuk, Lucian A., and Alma Cohen, 2005, The costs of entrenched boards, *Journal of Financial Economics* 78, 409-433.

Bebchuk, Lucian A., Alma Cohen, and Allen Ferrell, 2009, What matters in corporate governance?, *Review of Financial Studies* 22, 783-827.

Bebchuk, Lucian A., Alma Cohen, and Charles C.Y. Wang, 2013, Learning and the disappearing association between governance and returns, *Journal of Financial Economics* 108, 323-348.

Bebchuk, Lucian A., Scott Hirst, and June Rhee, 2013, Towards the declassification of S&P 500 boards, *Harvard Business Law Review* 3, 157-184.

Bekaert, Geert, Kenton Hoyem, Wei-Yin Hu, and Enrichetta Ravina, 2017, Who is internationally diversified? Evidence from the 401 (k) plans of 296 firms, *Journal of Financial Economics* 124, 86-112.

Belinfanti, Tamara C., 2008, The proxy advisory and corporate governance industry: The case for increased oversight and control, *Stanford Journal of Law, Business & Finance* 14, 384-439.

Bianchi, Daniele, Matthias Büchner, and Andrea Tamoni, 2021, Bond risk premiums with machine learning, *Review of Financial Studies* 34, 1046-1089.

Boone, Audra L., and Joshua T. White, 2015, The effect of institutional ownership on firm transparency and information production, *Journal of Financial Economics* 117, 508-533.

Breiman, Leo, 2001, Random forests, *Machine Learning* 45, 5-32.

Bushee, Brian J.1 2001, Do institutional investors prefer near-term earnings over long-run value? *Contemporary Accounting Research* 18, 207-246.

Bushee, Brian J., and Christopher F. Noe, 2000, Corporate disclosure practices, institutional investors, and stock return volatility, *Journal of Accounting Research* 38, 171-202.

Catan, Emiliano M., and Marcel Kahan, 2016, The law and finance of antitakeover statutes, *Stanford Law Review* 68, 629-682.

Cohen, Alma, and Charles CY Wang, 2013, How do staggered boards affect shareholder value? Evidence from a natural experiment, *Journal of Financial Economics* 110, 627-641.

Crane, Alan D., Sébastien Michenaud, and James P. Weston, 2016, The effect of institutional ownership on payout policy: Evidence from index thresholds, *Review of Financial Studies* 29, 1377-1408.

Cremers, Martijn, and Allen Ferrell, 2014, Thirty years of shareholder rights and firm value, *Journal of Finance* 69, 1167-1196.

Cremers, K.J. Martijn, Lubomir P. Litov, and Simone M. Sepe, 2017, Staggered boards and long-term firm value, revisited, *Journal of Financial Economics* 126, 422-444.

Cuñat, Vincente, Mireia Gine, and Maria Guadalupe, 2012, The vote is cast: The effect of corporate governance on shareholder value, *Journal of Finance* 67, 1943-1977.

Daines, Robert, Shelley Xin Li, and Charles C.Y. Wang, 2021, Can staggered boards improve value? Causal evidence from Massachusetts, *Contemporary Accounting Research* 38, 3053-3084.

Del Guercio, Diane, and Jennifer Hawkins, 1999, The motivation and impact of pension fund activism, *Journal of Financial Economics* 52, 293-340.

Denes, Matthew R., Jonathan M. Karpoff, and Victoria B. McWilliams, 2017, Thirty years of shareholder activism: A survey of empirical research, *Journal of Corporate Finance* 44, 405-424.

Díaz-Uriarte, Ramón, and Sara Alvarez de Andres, 2006, Gene selection and classification of microarray data using random forest, *BMC Bioinformatics* 7, 1-13.

Doidge, Craig, G. Andrew Karolyi, and René M. Stulz, 2017, The US listing gap, *Journal of Financial Economics* 123, 464-487.

Dyck, Alexander, Natalya Volchkova, and Luigi Zingales, 2008, The corporate governance role of the media: Evidence from Russia, *Journal of Finance* 63, 1093-1135.

Erel, Isil, Léa H. Stern, Chenhao Tan, and Michael S. Weisbach, 2021, Selecting directors using machine learning, *Review of Financial Studies* 34, 3226-3264.

Faleye, Olubunmi, 2007, Classified boards, firm value, and managerial entrenchment, *Journal of Financial Economics* 83, 501-529.

Field, Laura Casares, and Jonathan M. Karpoff, 2002, Takeover defenses of IPO firms, *Journal of Finance* 57, 1857-1889.

Field, Laura Casares, and Michelle Lowry, 2022, Bucking the trend: Why do IPOs choose controversial governance structures and why do investors let them?, *Journal of Financial Economics* 146, 27-54.

Frankel, Richard M., Jared N. Jennings, and Joshua A. Lee, 2022, Disclosure sentiment: Machine learning vs dictionary methods, *Management Science* 68, 5514-5532.

Ganor, Mira, 2008, Why do managers dismantle staggered boards, *Delaware Journal of Corporate Law* 33, 149-198.

Gompers, Paul A., Joy Ishii, and Andrew Metrick, 2003, Corporate governance and equity prices, *Quarterly Journal of Economics* 118, 107-156.

Gompers, Paul A., Joy Ishii, and Andrew Metrick, 2010, Extreme governance: An analysis of dual-class firms in the United States, *Review of Financial Studies* 23, 1051-1088.

Griffin, Caleb N., 2020, Margins: Estimating the influence of the big three on shareholder proposals, *SMU Law Review* 73, 409-444.

Gu, Shihao, Bryan Kelly, and Dacheng Xiu, 2020, Empirical asset pricing via machine learning, *Review of Financial Studies* 33, 2223-2273.

Guernsey, Scott, Simone M. Sepe, and Matthew Serfling, 2022, Blood in the water: The value of antitakeover provisions during market shocks, *Journal of Financial Economics* 143, 1070-1096.

Guo, Re-Jin, Timothy A. Kruse, and Tom Nohel, 2008, Undoing the powerful anti-takeover force of staggered boards, *Journal of Corporate Finance* 14, 274-288.

Hannes, Sharon, 2006, A demand-side theory of antitakeover defenses, *Journal of Legal Studies* 35, 475-524.

Heath, Davidson, Daniele Macciocchi, Roni Michaely, and Matthew C. Ringgenberg, 2022, Do index funds monitor?, *Review of Financial Studies* 35, 91-131.

Hirst, Scott, and Lucian A. Bebchuk, 2019, The specter of the giant three, *Boston University Law Review* 99, 721-741.

Iliev, Peter, Jonathan Kalodimos, and Michelle Lowry, 2021, Investors' attention to corporate governance, *Review of Financial Studies* 34, 5581-5628.

Ising, Elizabeth A., 2012, Corporate governance: Recent trends in board declassification, *INSIGHTS* 26, 13-21.

John, Kose, Dalida Kadyrzhanova, and Sangho Lee, 2021, Do classified boards deter takeovers? Evidence from merger waves, *Journal of Financial and Quantitative Analysis*, forthcoming.

Johnson, William C., Jonathan M. Karpoff, and Sangho Yi, 2015, The bonding hypothesis of takeover defenses: Evidence from IPO firms, *Journal of Financial Economics* 117, 307-332.

Johnson, William C., Jonathan M. Karpoff, and Sangho Yi, 2022, The life cycle effects of corporate takeover defenses, *Review of Financial Studies* 35, 2879-2927.

Kahle, Kathleen M., and René M. Stulz, 2017, Is the US public corporation in trouble?, *Journal of Economic Perspectives* 31, 67-88.

Karakaş, Oğuzhan, and Mahdi Mohseni, 2021, Staggered boards and the value of voting rights, *Review of Corporate Finance Studies* 10, 513-550.

Karpoff, Jonathan M., Paul H. Malatesta, and Ralph A. Walkling, 1996, Corporate governance and shareholder initiatives: Empirical evidence, *Journal of Financial Economics* 42, 365-395.

Karpoff, Jonathan M., Robert J. Schonlau, and Eric W. Wehrly, 2017, Do takeover defense indices measure takeover deterrence?, *Review of Financial Studies* 30, 2359-2412.

Karpoff, Jonathan M., Robert Schonlau, and Eric Wehrly, 2022, Which antitakeover provisions deter takeovers?, *Journal of Corporate Finance* 75, 102218.

Karpoff, Jonathan M., and Michael D. Wittry, 2023, Corporate takeover defenses. In: *Handbook of Corporate Finance*, forthcoming.

Kastiel, Kobi, and Yaron Nili, 2021, The corporate governance gap, *Yale Law Journal* 131, 782-860.

Klausner, Michael, 2013, Fact and fiction in corporate law and governance, *Stanford Law Review* 65, 1325-1370.

Law, Kelvin K.F., and Luo Zuo, 2021, How does the economy shape the financial advisory profession?, *Management Science* 67, 2466-2482.

Lewellen, Jonathan, and Katharina Lewellen, 2022, Institutional investors and corporate governance: The incentive to be engaged, *Journal of Finance* 77, 213-264.

Li, Kai, Feng Mai, Rui Shen, and Xinyan Yan, 2021, Measuring corporate culture using machine learning, *Review of Financial Studies* 34, 3265-3315.

Liaw, Andy, and Matthew Wiener, 2002, Classification and regression by randomForest, *R News* 2, 18-22.

Madden, John J., 2011, The shifting landscape of corporate governance, *Harvard Law School Forum on Corporate Governance*, April 10.

Malmendier, Ulrike, and Stefan Nagel, 2011, Depression babies: Do macroeconomic experiences affect risk taking?, *Quarterly Journal of Economics* 126, 373-416.

Malmendier, Ulrike, and Stefan Nagel, 2016, Learning from inflation experiences, *Quarterly Journal of Economics* 131, 53-87.

Malmendier, Ulrike, Geoffrey Tate, and Jon Yan, 2011, Overconfidence and early-life experiences: the effect of managerial traits on corporate financial policies, *Journal of Finance* 66, 1687-1733.

McCahery, Joseph A., Zacharias Sautner, and Laura T. Starks, 2016, Behind the scenes: The corporate governance preferences of institutional investors, *Journal of Finance* 71, 2905-2932.

McGurn, Patrick S., 2002, Classification cancels corporate accountability, *Stanford Law Review* 55, 839-844.

Miric, Milan, Nan Jia, and Kenneth G. Huang., 2023, Using supervised machine learning for large-scale classification in management research: The case for identifying artificial intelligence patents, *Strategic Management Journal* 44, 491-519.

Oyer, Paul, 2008, The making of an investment banker: Stock market shocks, career choice, and lifetime income, *Journal of Finance* 63, 2601-2628.

Parker, Jonathan A., Antoinette Schoar, Allison T. Cole, and Duncan Simester, 2022, Household portfolios and retirement saving over the life cycle, Working paper, MIT Sloan School of Management.

Prasad, Anantha M., Louis R. Iverson, and Andy Liaw, 2006, Newer classification and regression tree techniques: Bagging and random forests for ecological prediction, *Ecosystems* 9, 181-199.

Schmidt, Cornelius, and Rüdiger Fahlenbrach, 2017, Do exogenous changes in passive institutional ownership affect corporate governance and firm value? *Journal of Financial Economics* 124, 285-306.

Schoar, Antoinette, and Luo Zuo, 2017, Shaped by booms and busts: How the economy impacts CEO careers and management styles, *Review of Financial Studies* 30, 1425-1456.

Shleifer, Andrei, and Robert W. Vishny, 1986, Large shareholders and corporate control, *Journal of Political Economy* 94, 461-488.

Shleifer, Andrei, and Robert W. Vishny, 1997, A survey of corporate governance, *Journal of Finance* 52, 737-783.

Shotton, Jamie, Toby Sharp, Alex Kipman, Andrew Fitzgibbon, Mark Finocchio, Andrew Blake, Mat Cook, and Richard Moore, 2013, Real-time human pose recognition in parts from single depth images, *Communications of the ACM* 56, 116-124.

Strine, Leo E. Jr, 2014, Can we do better by ordinary investors; A pragmatic reaction to the dueling ideological mythologists of corporate law, *Columbia Law Review* 114, 449-502.

Strickland, Deon, Kenneth W. Wiles, and Marc Zenner, 1996, A requiem for the USA: Is small shareholder monitoring effective?, *Journal of Financial Economics* 40, 319-338.

Subramanian, Guhan, 2007, Board silly, *The New York Times*, February 14.

Svetnik, Vladimir, Andy Liaw, Christopher Tong, J. Christopher Culberson, Robert P. Sheridan, and Bradley P. Feuston, 2003, Random forest: A classification and regression tool for compound classification and QSAR modeling, *Journal of Chemical Information and Computer Sciences* 43, 1947-1958.

Thomas, Randall S., and James F. Cotter, 2007, Shareholder proposals in the new millennium: Shareholder support, board response, and market reaction, *Journal of Corporate Finance* 13, 368-391.

Varian, Hal R., 2014, Big data: New tricks for econometrics, *Journal of Economic Perspectives* 28, 3-28.

Appendix A. Example of the "Proposal No. 1" paragraph from an Annual Proxy Statement

Filing company: Information Advantage Software Inc

Central Index Key (CIK): 0001047118 Filing date: 5/19/1998

Standard industry classification (SIC): Services-Prepackaged Software [7372]

Form Type: DEF 14A[13]

INFORMATION ADVANTAGE, INC.

7905 GOLDEN TRIANGLE DRIVE, SUITE 190

EDEN PRAIRIE, MINNESOTA 55344-7227

PROXY STATEMENT

FOR

ANNUAL MEETING OF STOCKHOLDERS

TO BE HELD

JUNE 17, 1998

...

PROPOSAL NO. 1

ELECTION OF DIRECTORS

NOMINEES

The Board of Directors currently consists of eight members serving staggered three-year terms. Three persons, all of whom currently serve as Class I directors, have been nominated for election as Class I directors to serve three-year terms expiring in 2001 and until their successors have been duly elected and qualified. The five other directors have terms of office which do not expire in 1998. There are no family relationships between any director or officer.

It is intended that votes will be cast pursuant to the enclosed proxy for the election of the nominees listed in the table below, except for those proxies which withhold such authority. Stockholders do not have cumulative voting rights with respect to the election of directors, and proxies cannot be voted for a greater number of directors than the number of nominees. In the event that any of the nominees shall be unable or unwilling to serve as a director, it is intended that the proxy will be voted for the election of such other person or persons as the remaining directors may recommend in the place of such nominee. The Company has no reason to believe that any of the nominees will not be candidates or will be unable to serve.

VOTE REQUIRED

The three nominees receiving the highest number of affirmative votes of the shares entitled to vote at the Annual Meeting shall be elected to the Board of Directors as Class I directors. An abstention will have the same effect as a vote withheld for the election of directors and a broker non-vote will not be treated as voting in person or by proxy on the proposal. Set forth below is certain information concerning the three nominees for election as Class I directors and the five other directors whose terms of office will continue after the Annual Meeting. THE BOARD OF DIRECTORS RECOMMENDS THAT STOCKHOLDERS VOTE FOR THE NOMINEES LISTED BELOW.

[13] See https://www.sec.gov/Archives/edgar/data/1047118/0001047469-98-021169.txt

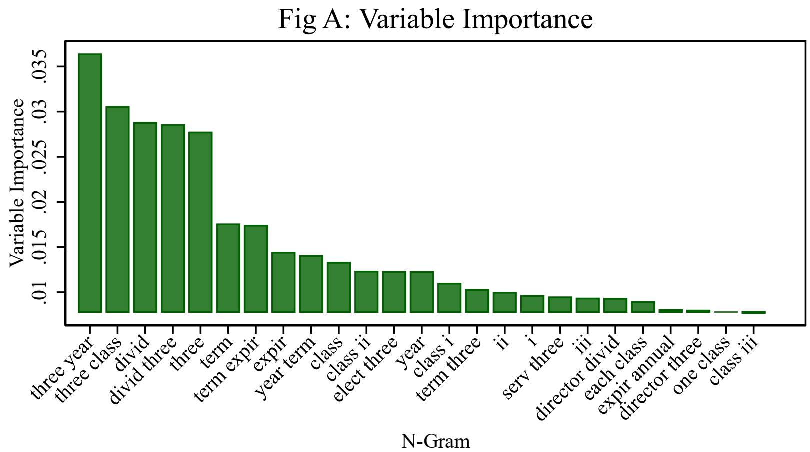
Appendix B. Variable Definitions

This table provides the definitions for the main variables used in this study. Variables used in auxiliary tests and not included here are defined in the corresponding table captions.

Variable	Definition (Compustat and CRSP variables are in italics when appropriate)
%MFVote	Total number of mutual funds that voted "for" a proposal to declassify the board divided by the total number of mutual funds that casted votes ("for" + "against" + "abstain").
%Vote	Total number of "for" votes to declassify a board divided by the total number of votes cast ("for" + "against" + "abstain").
Age	The number of years that a firm has been publicly traded, determined based on when a firm first has non-missing share price information in the Compustat database.
Assets	Book value of assets (*at*) (in millions and 2017 dollars).
Big 3 IO	Percentage of a firm's shares outstanding owned by the Big Three (i.e., Blackrock, State Street, and Vanguard) institutional investors at the end of a firm's fiscal year.
CAR [-1, +1] CAR [-2, +2]	Cumulative abnormal returns over the three- or five-day window surrounding the annual shareholder meeting date, where the meeting date is day zero. Parameters used to calculate CARs are estimated using the market model and CRSP equal-weighted index over the [-210,-11] trading days before the meeting date.
CB	Indicator variable equal to one if a firm has a classified board, and zero otherwise.
Declass	Indicator variable equal to one if a firm has a classified board in year *t*-1 and not a classified board in year *t*, and zero otherwise.
Delaware	Indicator variable that equals one if a firm is incorporated in Delaware, and zero otherwise.
Total IO	Percentage of a firm's shares outstanding owned by institutional investors at the end of a firm's fiscal year.
Quasi IO	Percentage of a firm's shares outstanding owned by quasi-indexer institutional investors at the end of a firm's fiscal year, as defined in Bushee and Noe (2000) and Bushee (2001).
Proposal	Indicator variable equal to one if a firm voted on a proposal to declassify its board during year *t*, and zero otherwise.
S&P 1500	Indicator variable equal to one if a firm is in the S&P 1500 Index, and zero otherwise. We combine several databases to identify a firm's historical membership in the S&P 1500. For observations beginning in 2007, we extract S&P 1500 membership from ISS. For data before 2007, we obtain index membership from the CRSP-Compustat historical header file CST_HIST and supplement potentially missing observations with the Compustat file SPIND.
Tobin's Q	Market value of assets (*prcc_f*csho+at-ceq*) scaled by book value of assets (*at*).

Figure 1
Variable Importance and N-Gram Overlap

Figure A tabulates the variable importance values of the top 25 N-Grams that predict a firm's classified board status. Figure B tabulates the fraction of S&P 1500 and non-S&P 1500 firms mentioning these N-Grams.



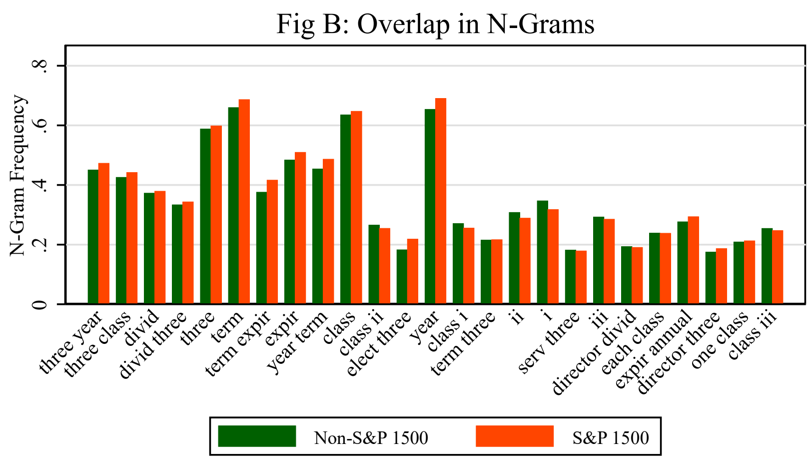


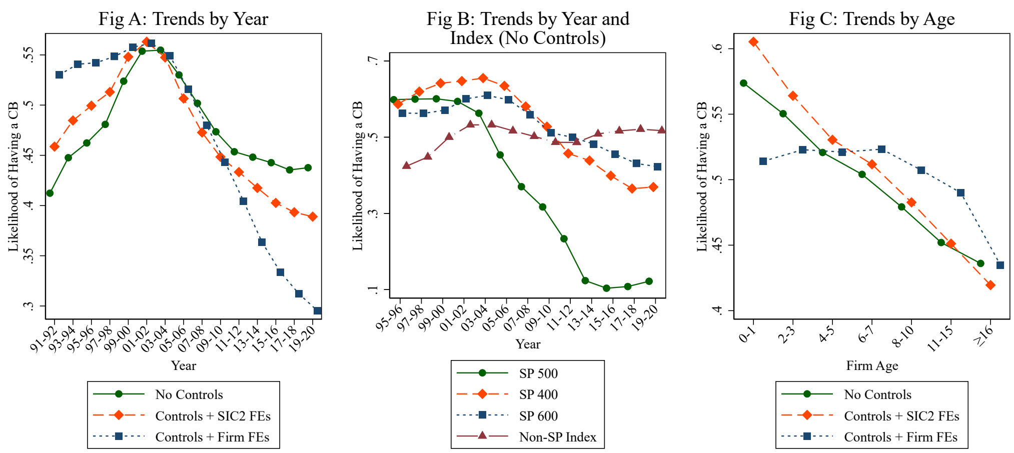
Figure 2
Use of Classified Boards by Year and Firm Age

The figures show the fraction of firms with a classified board by year and firm age. The figures plot the coefficient estimates (β_{1991}-β_{2020} and ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of the classified board indicator (*CB*) on controls:

$$CB_{it} = \sum_{t=1991}^{2020} \beta_t Year_t \left(or \sum_{a=0}^{\geq 16} \omega_a Age_{it} \right) + \Gamma X_{it} + \eta_k + \gamma_i + \varepsilon_{it}.$$

$Year_t$ equals one for observations in year group t, and zero otherwise. Age_{it} equals one if firm age is in age group a, and zero otherwise. In Panel B, regressions are estimated separately for each age group. X_{it} are firm-level characteristics, defined in Appendix B, that include $Ln(Assets_{t\text{-}1})$, IO_t, $Delaware_t$, and $S\&P\ 1500_t$. η_k and γ_i are two-digit SIC industry and firm fixed effects, respectively.

Panel A: Use of CB by Year and Firm Age



Panel B: Use of CB Over Time by Firm Age

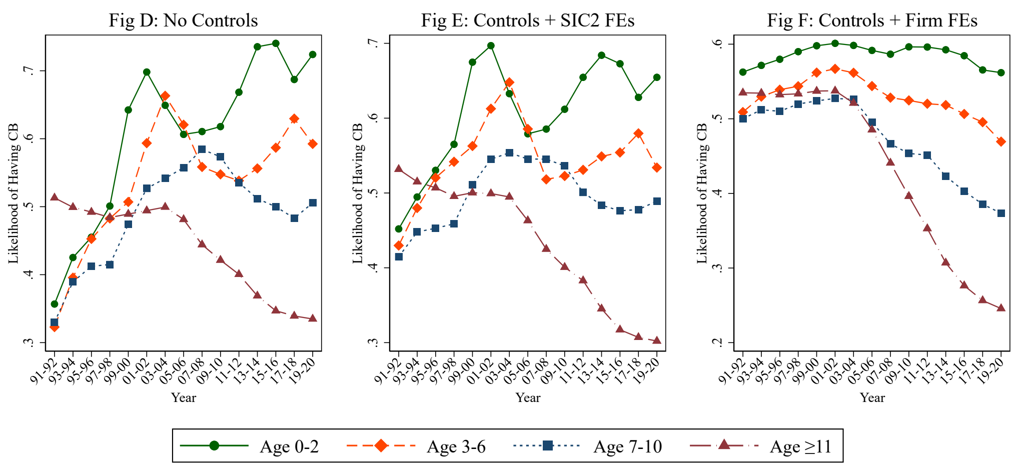


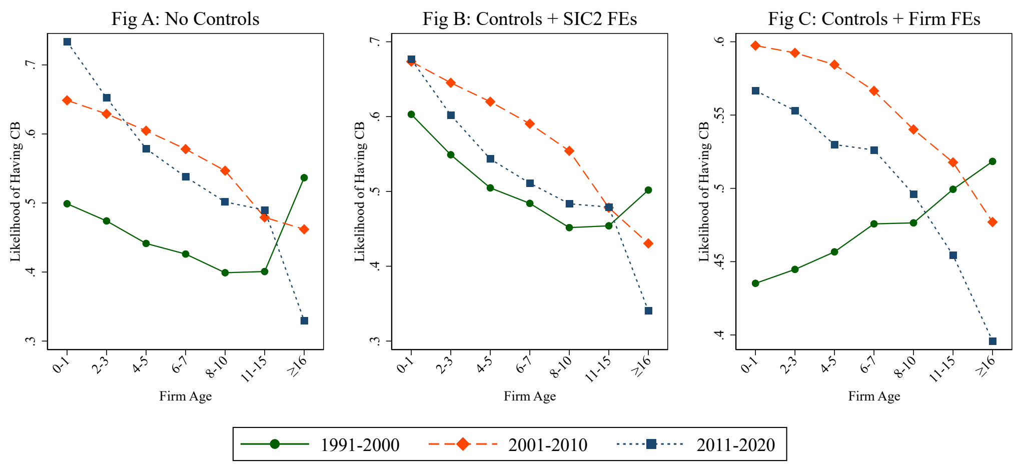
Figure 3
Use of Classified Boards by Firm Age, Decade, and IPO Cohort

Panel A (B) shows the fraction of firms with a classified board by firm age group and decade (IPO cohort). The figures plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of the classified board indicator (*CB*) on controls, where regressions are estimated separately for each decade in Panel A (IPO cohort in B):

$$CB_{it} = \sum_{a=0}^{\geq 16} \omega_a Age_{it} + \Gamma X_{it} + \eta_k + \gamma_i + \varepsilon_{it}.$$

Age_{it} equals one if firm age is in age group a, and zero otherwise. X_{it} are firm-level characteristics, defined in Appendix B, that include $Ln(Assets_{t-1})$, IO_t, $Delaware_t$, and $S\&P\ 1500_t$. η_k and γ_i are two-digit SIC industry and firm fixed effects, respectively.

Panel A: Use of CB by Firm Age and Decade



Panel B: Use of CB by Firm Age and IPO Cohort

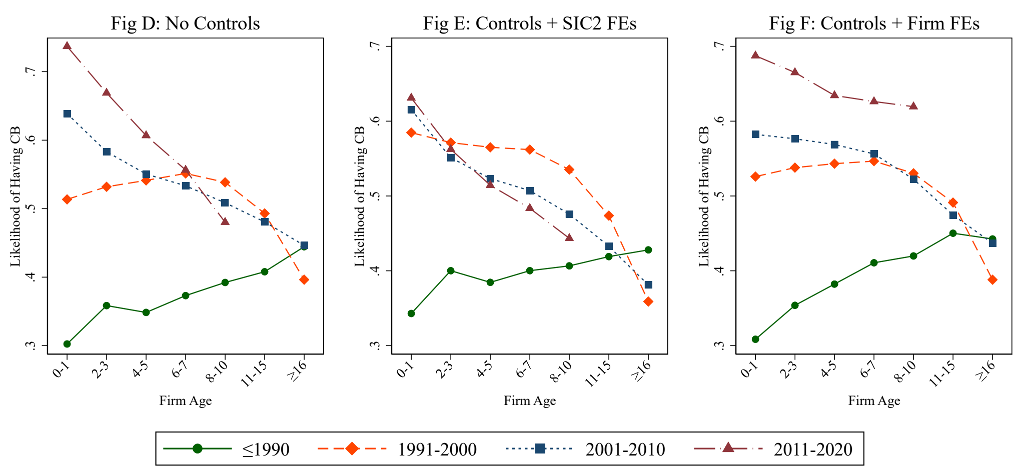


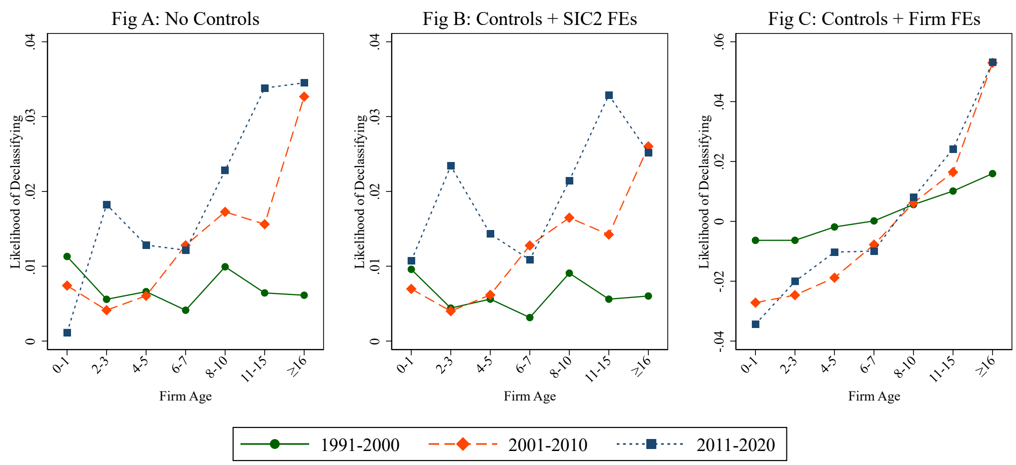
Figure 4
Likelihood of Declassifying Board by Firm Age, Decade, and IPO Cohort

Panel A (B) shows the likelihood of a firm declassifying its board over time by firm age group and decade (IPO cohort). The figures plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of the board declassification indicator variable (*Declass*) on controls, where regressions are estimated separately for each decade in Panel A (IPO cohort in Panel B):

$$CB_{it} = \sum_{a=0}^{\geq 16} \omega_a Age_{it} + \Gamma X_{it} + \eta_k + \gamma_i + \varepsilon_{it}.$$

Age_{it} equals one if firm age is in age group a, and zero otherwise. X_{it} are firm-level characteristics, defined in Appendix B, that include $Ln(Assets_{t\text{-}1})$, IO_t, $Delaware_t$, and $S\&P\ 1500_t$. η_k and γ_i are two-digit SIC industry and firm fixed effects, respectively.

Panel A: Likelihood of Declassifying by Firm Age and Decade



Panel B: Likelihood of Declassifying by Firm Age and IPO Cohort

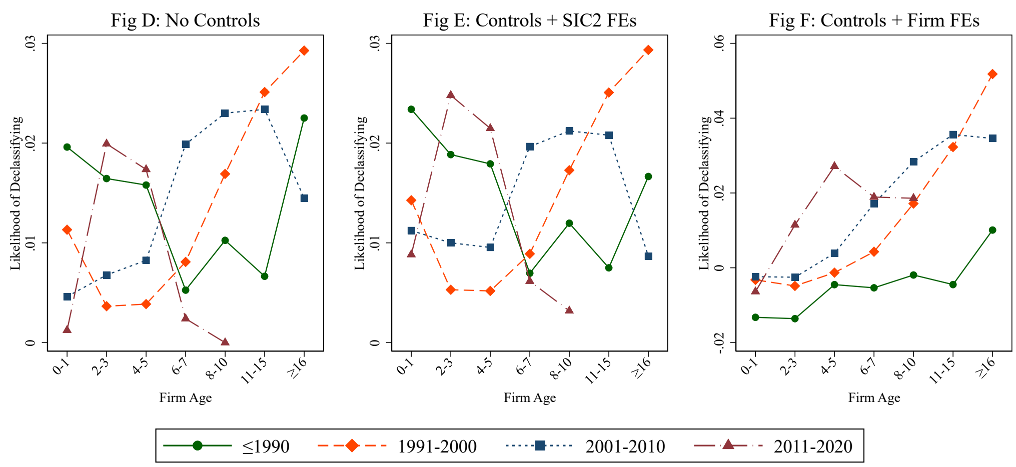


Figure 5
WSJ and Academic Articles

Figure A plots the number of articles published in the Wall Street Journal (WSJ) that cover corporate scandals and shareholder activism and corporate governance from 1998 to 2020. 1998 is the earliest year we have WSJ article text. To identify relevant articles on corporate scandals, we identify WSJ articles that include the following keywords: "corporate scandal," "financial scandal," "accounting scandal," "business scandal," "corporate misconduct," "accounting fraud," and "financial fraud." Relevant articles on shareholder activism and corporate governance must have the phrase "corporate governance" and one of the following keywords: "shareholder activism," "activist investor," "activist shareholder," "shareholder activist", "proxy fight", "proxy contest", and "proxy battle." Figure B plots the number of academic articles on classified boards from 1996 to 2020, which are those with either of the keywords "classified board(s)" or "staggered board(s)."

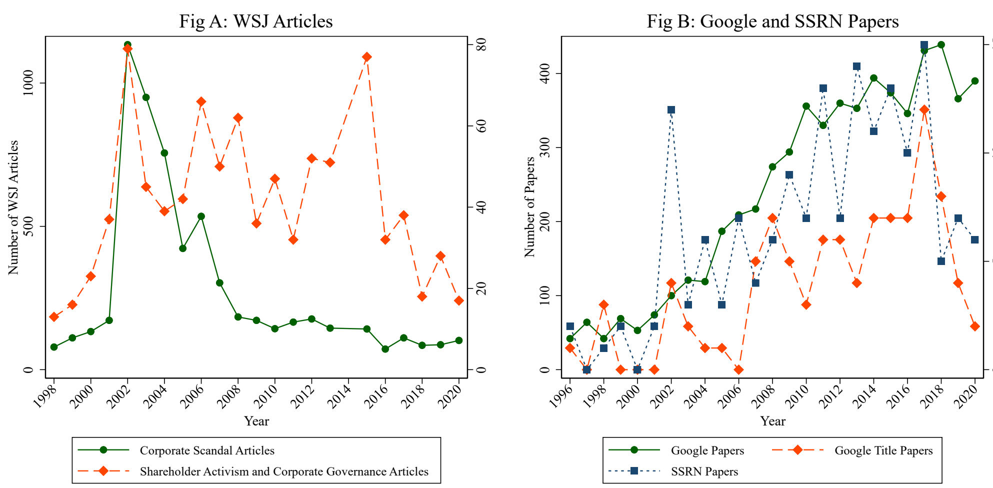


Figure 6
Institutional Ownership by Year

This figure plots the fraction of a firm's shares owned by institutional investors from 1991 to 2020. *Total IO* is the fraction of a firm's shares owned by all institutional investors. *Quasi IO* is the fraction of a firm's shares owned by institutional investors labeled as quasi-indexers in Bushee and Noe (2000) and Bushee (2001). *Big 3 IO* is fraction of a firm's shares owned by the Big Three institutional investors (Blackrock, State Street, Vanguard).

$$Total\ IO_{it}\ or\ Quasi\ IO_{it}\ or\ Big\ 3\ IO_{it} = \sum_{t=1991}^{2020} \beta_t Year_t + \Gamma X_{it} + \eta_k + \gamma_i + \varepsilon_{it}.$$

$Year_t$ equals one for observations in year group t, and zero otherwise. X_{it} are firm-level characteristics, defined in Appendix B, that include $Ln(Assets_{t\text{-}1})$, $Delaware_t$, and $S\&P\ 1500_t$. η_k and γ_i are two-digit SIC industry and firm fixed effects, respectively.

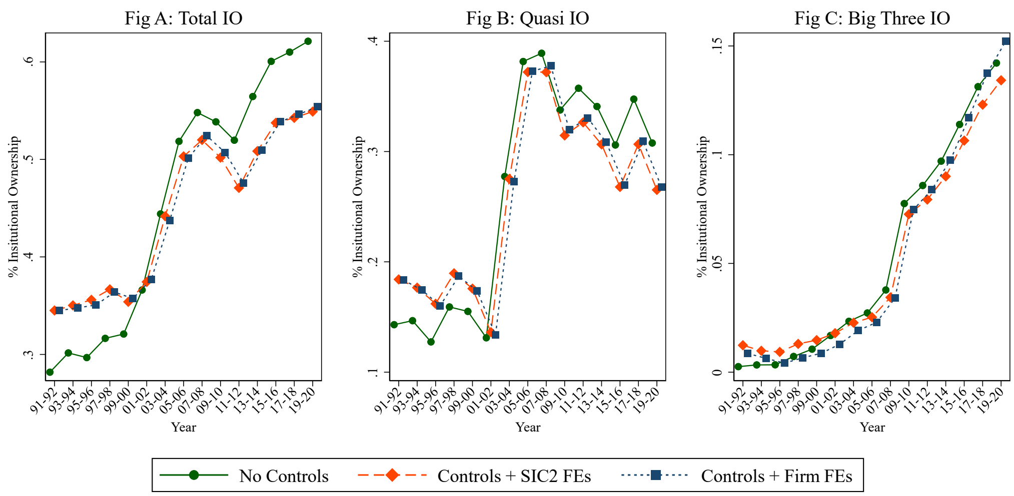


Figure 7
Proposals to Declassify by Year

Figures A-C tabulate the likelihood of firms receiving proposals to declassify their board (*Proposal*), the fraction of shares "for" declassifying a firm's board (*%Vote*), and fraction of mutual funds that voted "for" declassifying a firm's board (*%MFVote*), respectively, over the period 2003 to 2020. In Figure A, firms must have a classified board in year *t* or *t*-1 to enter the sample. The figures plot the coefficient estimates (β_{2003}-β_{2020}) from their respective versions of the following OLS regression:

$$Proposal_{it} \text{ or } \%Vote_{it} \text{ or } \%MFVote_{it} = \sum_{t=2003}^{2020} \beta_t Year_t + \Gamma X_{it} + \eta_k + \gamma_i + \varepsilon_{it}.$$

$Year_t$ equals one for observations in year group *t*, and zero otherwise. X_{it} are firm-level characteristics, defined in Appendix B, that include $Ln(Assets_{t-1})$, IO_t, $Delaware_t$, and $S\&P\ 1500_t$. η_k and γ_i are two-digit SIC industry and firm fixed effects, respectively.

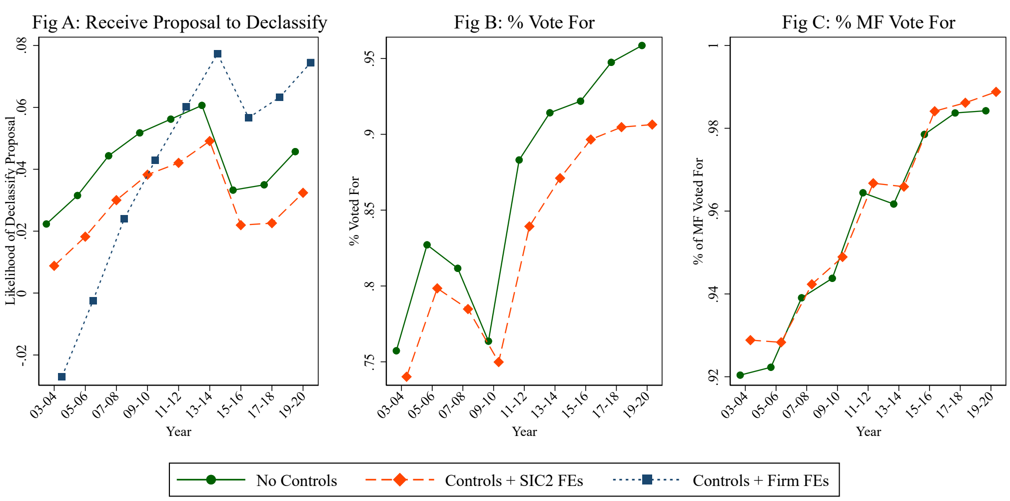


Figure 8
Effect of being Added to the S&P 1500 on Classified Board Usage by Time and Firm Age

Figures A-D plot the coefficient estimates (β_{-3}- β_3) from OLS regressions using a propensity score matched sample examining the effect of joining the S&P 1500 on the likelihood of having a classified board during the following treatment cohorts: 1991-2000, 2001-2010, and 2011-2020. The regression is:

$$CB_{ijt} = \sum_{t=-3}^{3} \beta_t(Treat_{ij} \times Time_{jt}) + \gamma_{ij} + \delta_{jt} + \Gamma X_{ij} \times Post_{jt} + \varepsilon_{ijt}.$$

The dependent variable CB_{ijt} equals one if firm i for treatment cohort j in year t has a classified board, and zero otherwise. $Treat_{ij}$ equals one for the treatment firms that are added to the S&P 1500 Index, and zero otherwise. $Time_{tj}$ equals one for observations in period t relative to the treatment year for treatment cohort j, and zero otherwise. $Time_{jt\text{-}1}$ is the excluded base year. γ_{ij} are firm-treatment cohort fixed effects, and δ_{jt} are treatment cohort-year fixed effects. X_{it} are firm-level characteristics fixed at time t-1 for each treatment cohort j and defined in Appendix B that include *Ln*(*Assets*), *IO*, and *Delaware*. $Post_{jt}$ equals one for the years t to t+3 after the treatment year for treatment cohort j, and zero otherwise. 90% confidence intervals based on standard errors clustered by firm-treatment cohort are reported.

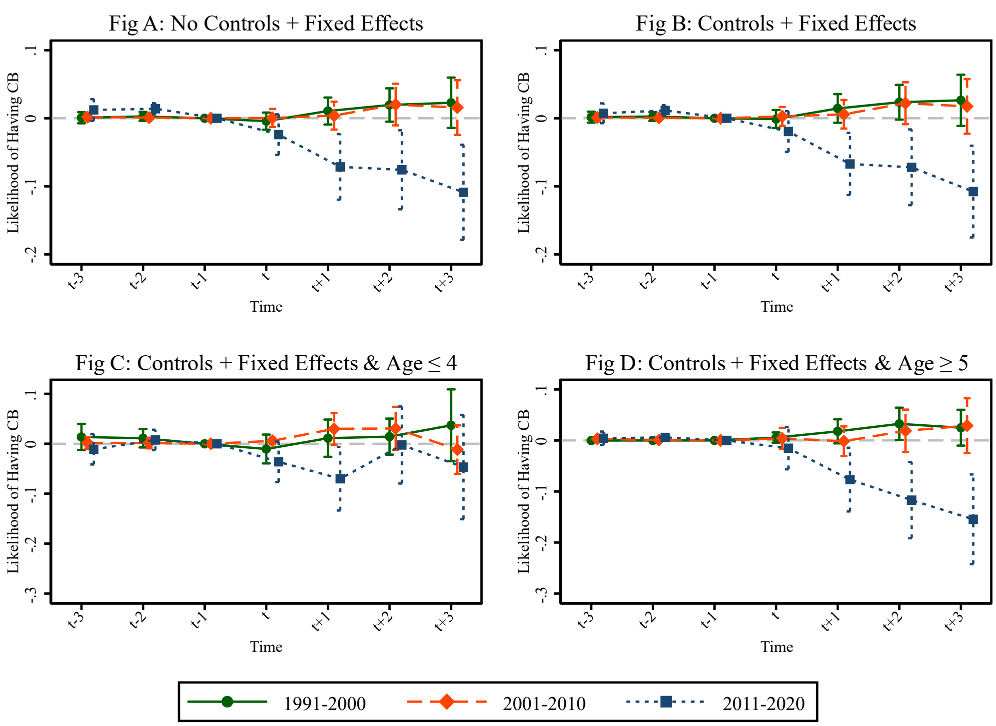


Figure 9
Announcement CARs to Board Declassification over Time

Figures A and B tabulate ±1-day and ±2-day CARs around annual shareholder meetings that vote to declassify a firm's board, respectively, over the period 1995 to 2020. Parameters used to calculate CARs are estimated using the market model and CRSP equal-weighted index over the [-210,-11] trading days before the meeting date. The figures plot the coefficient estimates (β_{1995}-β_{2020}) from their respective versions of the following OLS regression:

$$CAR[-1,+1] \; or \; CAR[-2,+2] = \sum_{t=1995}^{2020} \beta_t Year_t + \Gamma X_{it} + \eta_k + \varepsilon_{it}.$$

$Year_t$ equals one for observations in year group t, and zero otherwise. X_{it} are firm-level characteristics, defined in Appendix B, that include *Ln*($Assets_{t-1}$), IO_t, $Delaware_t$, and *S&P 1500*$_t$. η_k are two-digit SIC industry fixed effects. 90% confidence intervals based on standard errors clustered by firm are reported.

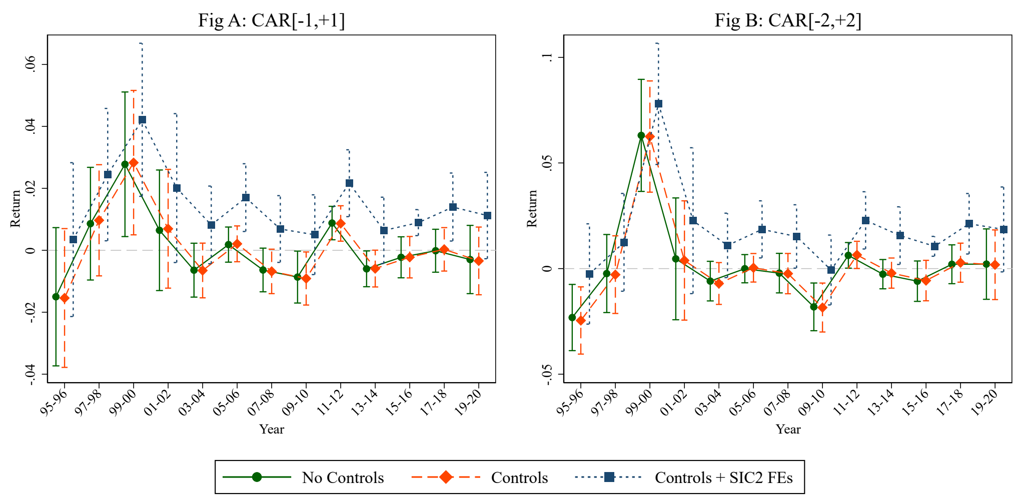


Table 1
Summary Statistics: Comparing Firms with Classified and Unitary Boards

This table reports summary statistics for the main variables used in our analyses over the period 1991 to 2020. Continuous variables are winsorized at their 1st and 99th percentiles. Significant differences at the 10%, 5%, and 1% levels, respectively, in means and medians between the Classified Board and Unitary Board samples are denoted with *, **, and *** in the Mean and P50 columns for the Classified Board sample. Standard errors are clustered by firm. Variables are defined in Appendix B.

	Classified Board Sample (Obs = 65,569)			Unitary Board Sample (Obs = 70,525)		
	Mean	P50	Std Dev	Mean	P50	Std Dev
Assets	3117.6***	519.6***	9716.2	5235.5	293.0	16366.4
Ln(Assets)	6.243***	6.253***	1.938	5.866	5.680	2.431
IO	0.457***	0.443***	0.305	0.414	0.363	0.330
Delaware	0.575***	1.000	0.494	0.541	1.000	0.498
S&P 1500	0.291	0.000	0.454	0.286	0.000	0.452
Age	13.70***	10.00***	12.42	16.08	12.00	13.52
Ln(Age)	2.261***	2.398***	1.014	2.458	2.565	0.969

Table 2
The Use of Classified Boards by Firm Age, Decade, and IPO Cohort

Column 1 shows the fraction of firms with a classified board by firm age group. Columns 2-4 (5-8) show the fraction of firms with a classified board by firm age group and decade (IPO cohort). The table tabulates the coefficient estimates (ω_2-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of the classified board indicator (*CB*) on controls, where regressions are estimated separately for each decade in columns 2-4 (IPO cohort in columns 5-8). In these tests, the youngest firms aged 0-1 are the excluded reference group and are analogous to Figures 3C.

$$CB_{it} = \sum_{a=2}^{\geq 16} \omega_a Age_{it} + \Gamma X_{it} + \gamma_i + \varepsilon_{it}.$$

Age_{it} equals one if firm age is in age group a, and zero otherwise. X_{it} are firm-level characteristics, defined in Appendix B, that include $Ln(Assets_{t-1})$, IO_t, $Delaware_t$, and $S\&P\ 1500_t$. γ_i are firm fixed effects. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Full Sample		Decade			IPO Cohort		
	1991-2020	1991-2000	2001-2010	2011-2020	≤1990	1991-2000	2001-2010	2011-2020
Age	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2-3	0.009***	0.009***	-0.005	-0.014***	0.045**	0.012***	-0.006	-0.022***
	(3.34)	(3.10)	(-1.37)	(-3.03)	(2.31)	(3.35)	(-1.37)	(-4.76)
4-5	0.007*	0.021***	-0.013**	-0.037***	0.074***	0.017***	-0.013**	-0.053***
	(1.82)	(4.40)	(-2.37)	(-4.61)	(2.82)	(3.50)	(-2.01)	(-5.98)
6-7	0.009*	0.041***	-0.031***	-0.040***	0.102***	0.021***	-0.026***	-0.061***
	(1.90)	(6.46)	(-4.05)	(-4.20)	(3.73)	(3.36)	(-2.78)	(-5.29)
8-10	-0.007	0.041***	-0.057***	-0.071***	0.111***	0.004	-0.060***	-0.068***
	(-1.12)	(5.31)	(-6.19)	(-5.80)	(3.93)	(0.56)	(-4.96)	(-3.50)
11-15	-0.024***	0.064***	-0.080***	-0.112***	0.142***	-0.035***	-0.108***	
	(-3.02)	(6.92)	(-7.49)	(-7.68)	(4.82)	(-3.33)	(-6.77)	
≥ 16	-0.079***	0.083***	-0.120***	-0.171***	0.134***	-0.138***	-0.145***	
	(-7.56)	(6.95)	(-9.24)	(-10.20)	(4.33)	(-9.58)	(-6.04)	
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	135,391	54,211	44,670	35,000	61,647	51,985	14,910	6,849
Adj R^2	0.821	0.929	0.899	0.917	0.774	0.844	0.897	0.937

Table 3
Institutional Ownership, Firm Age, and Classified Board Usage Over Time

This table reports the fraction of firms with a classified board over time by firm age group and institutional ownership. The regressions tabulate the coefficient estimates (β_{1991}-β_{2020}) from their respective versions of the following OLS regression of the classified board indicator (*CB*) on controls:

$$CB_{it} = \sum_{t=1991}^{2020} \beta_t (Total\ IO_{it} \times Year_t) \left(or \sum_{t=1991}^{2020} [\beta_t (IndexIO_{it} \times Year_t) + \kappa_t (NonIndexIO_{it} \times Year_t)] \right) + \Gamma X_{it} + \gamma_i + \tau_t + \varepsilon_{it},$$

where regressions are estimated separately for each firm age group. $Year_t$ equals one for observations in year group *t*, and zero otherwise. *Total IO* equals the fraction of a firm's shares owned by all institutional investors. *IndexIO* equals the fraction of a firm's shares owned by index funds (quasi-indexers or the Big Three). *NonIndexIO* equals the fraction of a firm's shares owned by non-index institutional owners. *CS* equals one of the three cross-sectional variables. All institutional ownership variables are normalized to have a standard deviation of one to ease comparisons. X_{it} are firm-level characteristics, defined in Appendix B, that include $Ln(Assets_{t-1})$, $Delaware_t$, and $S\&P\ 1500_t$. γ_i and τ_t are firm and year fixed effects. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	CS = Total IO				CS = Quasi IO				CS = Big Three IO			
Age	0-2	3-6	7-10	≥11	0-2	3-6	7-10	≥11	0-2	3-6	7-10	≥11
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
91-95 × CS	-0.000	0.013*	0.010**	0.108***	-0.000	0.001	0.002	0.102***	-0.001	0.006	0.001	0.092***
	(-0.02)	(1.88)	(2.11)	(9.99)	(-0.07)	(0.21)	(0.21)	(9.83)	(-0.21)	(0.26)	(0.07)	(4.30)
96-00 × CS	0.002	0.007	0.014***	0.080***	0.004	0.003	0.004	0.077***	-0.010	0.009	0.018	0.110***
	(0.49)	(1.59)	(2.60)	(9.32)	(1.08)	(0.97)	(0.75)	(10.14)	(-1.30)	(0.43)	(1.64)	(5.45)
01-05 × CS	-0.001	0.001	0.016***	0.046***	0.003	0.002	0.013**	0.036***	0.002	0.007	0.033**	0.098***
	(-0.32)	(0.33)	(2.73)	(6.76)	(0.89)	(0.65)	(2.57)	(6.62)	(0.18)	(0.61)	(2.15)	(5.91)
06-10 × CS	-0.001	0.006	0.001	0.006	0.001	0.003	-0.002	0.011**	-0.014	-0.010	0.003	-0.028***
	(-0.63)	(1.34)	(0.21)	(0.98)	(0.42)	(0.83)	(-0.33)	(2.20)	(-1.57)	(-1.54)	(0.28)	(-3.87)
11-15 × CS	0.004	-0.000	-0.003	-0.026***	0.004	-0.007	0.002	-0.012**	0.004	-0.018**	-0.002	-0.064***
	(0.91)	(-0.13)	(-0.45)	(-4.33)	(1.01)	(-1.59)	(0.29)	(-2.25)	(1.04)	(-2.40)	(-0.24)	(-7.68)
16-20 × CS	-0.002	-0.008	-0.016*	-0.055***	-0.006	-0.005	-0.007	-0.034***	0.007**	-0.009	-0.001	-0.048***
	(-0.42)	(-1.60)	(-1.67)	(-7.47)	(-1.13)	(-1.27)	(-1.00)	(-4.29)	(2.07)	(-1.64)	(-0.17)	(-6.56)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	18,994	24,423	18,970	69,468	18,994	24,423	18,970	69,468	18,994	24,423	18,970	69,468
Adj R^2	0.971	0.961	0.960	0.819	0.971	0.961	0.960	0.819	0.971	0.961	0.960	0.821

Table 4
S&P 1500 Membership, Firm Size, Firm Age, and Classified Board Usage Over Time

This table reports the fraction of firms with a classified board over time by firm age group and S&P 1500 Index membership or firm size. The regressions tabulate the coefficient estimates (β_{1991}-β_{2020}) from their respective versions of the following OLS regression of the classified board indicator (*CB*) on controls:

$$CB_{it} = \sum_{t=1991}^{2020} \beta_t (S\&P\ 1500 \times Year_t) \left(or \sum_{t=1991}^{2020} \beta_t (Firm\ Size_{it} \times Year_t) \right) + \Gamma X_{it} + \gamma_i + \tau_t + \varepsilon_{it},$$

where regressions are estimated separately for each firm age group. $Year_t$ equals one for observations in year group t, and zero otherwise. *S&P 1500* is an indicator variable equal to one if a firm is in the S&P 1500 Index, and zero otherwise. *Firm Size* is the natural logarithm of a firm's book value of assets. *Firm Size* is normalized to have a standard deviation of one to ease comparisons. *CS* equals one of the two cross-sectional variables. X_{it} are firm-level characteristics, defined in Appendix B, that include $Ln(Assets_{t-1})$ (not in columns 5-8), $Delaware_t$, IO_t, and $S\&P\ 1500_t$ (not in columns 1-4). γ_i and τ_t are firm and year fixed effects. t-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	CS = S&P 1500				CS = Ln(Assets)			
Age	0-2	3-6	7-10	≥11	0-2	3-6	7-10	≥11
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
91-95 × CS	0.007	-0.018	0.001	0.131***	0.010**	0.048***	0.034***	0.110***
	(0.37)	(-1.60)	(0.05)	(10.11)	(2.09)	(4.24)	(3.08)	(7.70)
96-00 × CS	-0.011	0.006	0.015	0.107***	0.008*	0.040***	0.036***	0.095***
	(-1.04)	(0.64)	(1.56)	(9.30)	(1.83)	(4.58)	(3.40)	(7.13)
01-05 × CS	-0.005	0.005	0.017	0.089***	-0.001	0.038***	0.023*	0.074***
	(-1.39)	(0.63)	(1.38)	(7.71)	(-0.20)	(4.59)	(1.96)	(5.83)
06-10 × CS	-0.011	0.005	0.001	-0.011	-0.006	0.019*	-0.008	0.010
	(-1.13)	(0.41)	(0.07)	(-0.93)	(-0.92)	(1.77)	(-0.71)	(0.80)
11-15 × CS	-0.011	-0.019*	-0.012	-0.117***	0.014**	0.005	-0.011	-0.052***
	(-0.92)	(-1.80)	(-0.68)	(-8.38)	(2.46)	(0.52)	(-0.75)	(-3.82)
16-20 × CS	0.005	-0.029**	-0.011	-0.160***	0.010*	-0.006	-0.017	-0.070***
	(1.07)	(-2.27)	(-0.55)	(-10.38)	(1.74)	(-0.61)	(-1.15)	(-4.94)
Controls	✓	✓	✓	✓	✓	✓	✓	`✓
Observations	18,994	24,423	18,970	69,468	18,994	24,423	18,970	69,468
Adj R^2	0.971	0.961	0.960	0.821	0.971	0.961	0.960	0.825

Table 5
Classified Boards and Tobin's Q

This table reports the results from OLS regressions relating firm value to classified boards over the period 1991-2020 (Panel A), 1991-2000 (Panel B), 2001-2010 (Panel C), and 2011-2020 (Panel D). The dependent variable *Tobin's Q* is the market value of assets scaled by the book value of assets. *CB* equals one if a firm has a classified board in year *t*, and zero otherwise. Each column tabulates regressions of firms in the same age group. Control variables defined in Appendix B and included in all regressions are $Ln(Assets_{t\text{-}1})$, IO_t, $Delaware_t$, and $S\&P\ 1500_t$. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Sample period 1991-2020

	Age 0 (1)	Age 1 (2)	Age 2 (3)	Age 3-4 (4)	Age 5-6 (5)	Age 7-9 (6)	Age ≥ 10 (7)
CB	0.157***	-0.041	-0.099**	-0.154***	-0.129***	-0.109***	-0.094***
	(2.70)	(-0.88)	(-2.24)	(-3.89)	(-3.30)	(-2.86)	(-3.61)
Year & SIC2 FEs	✓	✓	✓	✓	✓	✓	✓
Observations	6,213	7,373	7,377	13,693	12,123	15,425	74,464
Adj R^2	0.296	0.232	0.249	0.253	0.236	0.229	0.179

Panel B: Sample period 1991-2000

	Age 0	Age 1	Age 2	Age 3-4	Age 5-6	Age 7-9	Age ≥ 10
CB	0.149**	-0.071	-0.100*	-0.179***	-0.160***	-0.176***	-0.142***
	(2.03)	(-1.15)	(-1.68)	(-3.24)	(-2.70)	(-2.84)	(-4.27)
Year & SIC2 FEs	✓	✓	✓	✓	✓	✓	✓
Observations	4,044	4,372	4,073	6,952	5,537	6,458	24,359
Adj R^2	0.328	0.231	0.237	0.255	0.236	0.228	0.153

Panel C: Sample period 2001-2010

	Age 0	Age 1	Age 2	Age 3-4	Age 5-6	Age 7-9	Age ≥ 10
CB	0.233*	0.034	-0.092	-0.059	-0.145**	-0.073	-0.129***
	(1.84)	(0.34)	(-1.16)	(-0.91)	(-2.33)	(-1.37)	(-4.03)
Year & SIC2 FEs	✓	✓	✓	✓	✓	✓	✓
Observations	1,044	1,534	1,941	4,248	4,230	6,170	26,196
Adj R^2	0.232	0.194	0.248	0.301	0.261	0.251	0.199

Panel D: Sample period 2011-2020

	Age 0	Age 1	Age 2	Age 3-4	Age 5-6	Age 7-9	Age ≥ 10
CB	0.241	-0.027	-0.121	-0.208**	-0.013	-0.044	-0.023
	(1.53)	(-0.22)	(-0.97)	(-2.00)	(-0.14)	(-0.45)	(-0.51)
Year & SIC2 FEs	✓	✓	✓	✓	✓	✓	✓
Observations	1,102	1,453	1,349	2,486	2,353	2,794	23,907
Adj R^2	0.224	0.245	0.275	0.238	0.243	0.236	0.202

THIRTY YEARS OF CHANGE: THE EVOLUTION OF CLASSIFIED BOARDS

INTERNET APPENDIX

Scott Guernsey, Feng Guo, Tingting Liu, and Matthew Serfling

IA.1. Predicting Classified Board Status using the RF Classifier

IA.1.1. Sample selection

A focal contribution of our study is to demonstrate a novel application of machine learning – in particular, the Random Forest (RF) Classifier – that uses data from an existing database to extrapolate data points with a high degree of accuracy to a broader sample not covered by the database. To implement the RF Classifier algorithm, we start by obtaining all DEF 14A filings for all firms in SEC EDGAR through 2020, producing 179,942 unique CIK-FDATE pairs. After cleaning the data and merging the data to the CRSP-Compustat database, our final sample has 110,176 unique firm-year observations. Table IA.1 summarizes how each cleaning and merging step affected our sample.

Table IA.1
Sample Selection

Procedure	Observations
Start with all DEF 14A filings.	179,942
Require filings to have non-missing information for CIK codes and filing dates. The filing must also mention the word “elect” or “stagger” at least once.	176,868
Merge SEC Analytics Suite’s GVKEY-CIK link file to obtain each firm’s GVKEY. We only keep GVKEY-CIK links with a validation code/flag of 2 or 3.	168,943
Merge PERMNO from the CRSP-Compustat link file and require firms to have a non-missing historical (backfilled when necessary) SIC industry code.	136,165
When a GVKEY is linked to more than one CIK in a year, keep the CIK that matches the header (most recent) CIK in the Compustat file.	133,940
When a GVKEY has more than one DEF 14A filing in a year, keep the filing that falls around the “normal” filing month, which is the +/- 1-month around the mode filing month. If no filings fall in this window during a year, keep the earliest filed DEF 14A.	130,510
Drop firms with a two-digit SIC code of 67: “Holding & Other Investment Offices”.	110,511
Manually check all instances when our predictions do not match those in the ISS database and when a firm changes to or from having a classified board. Remove invalid observations and keep one observation for each GVKEY-FYEAR.	110,176

After extracting each raw text file from EDGAR for the 179,942 DEF 14A filings, we follow standard procedures to remove ASCII-Encoded segments (e.g., <TYPE> tags of GRAPHIC, PDF, and EXCEL) and HTML tags with Python Beautiful Soup. We collect the relevant text that we use as inputs in the RF Classifier algorithm in five steps:

Our first step is to identify valid DEF 14A filings that discuss the election of directors and obtain the relevant text. We start by requiring a DEF 14A to mention the word "elect" or "stagger" at least once to be included in the initial sample. This step reduces the sample to 176,868 DEF 14A filings. In order to further identify the relevant text related to the election of directors, we use regular expressions to locate 150 words immediately following "Proposal 1. Election of Directors." This is the paragraph that discusses how many directors are up for election in a year and whether there is more than one class of directors serving for more than one-year terms. There are a few variations of how the heading of the director election section can appear, such as "1. Election of Director", "Proposal No. 1 Election of Director", "Item 1. Election of Directors", etc, which are all captured by our regular expressions. Because this process can return more than one match if the DEF 14A mentions "Election of Directors" several times, we determine the best potential match by counting the number of lines and words in each match. We keep the match with the most words per line, potentially eliminating the matches in the table of contents section. Using this approach, we identify the election of directors paragraphs for 82.25% of the DEF 14A filings. Appendix A presents an example of a proxy statement filed through the SEC EDGAR system with the accompanying text under "Proposal No. 1 Election of Directors".

A concern is that regular expressions cannot capture all potential variants of "election of directors" mentioned in DEF 14As because language is dynamic and not all firms follow the same disclosure format. Thus, our second step is to conduct two specific keyword searches that would indicate the presence of a classified board. First, we search the DEF 14A filings for variations of the word "class" and then keep the ten words before and after each instance the keyword is found. We require the word "director" or "board" to appear within these ten words for us to consider it a valid keyword match. This restriction is intended to remove instances where "class" refers to share classes. Next, we search the DEF 14A filings for variations of the word "term" and then keep the ten words before and after each instance the keyword is found. We require the word "director" or "board", as well as the phrase "[number] [optional non-word character] year" or "stagger", to appear within these ten words for us to consider it a valid keyword match. This last criterion is designed to capture instances when a firm mentions directors having "three-year terms" and other variations of this phrasing. We identify at least one of these keywords for 66.0% of the sample. These keywords are found in 59.1% of the sample that we could not identify the election of directors paragraphs described earlier. We then combine all the paragraphs and texts into one corpus for each CIK-FDATE pair observation.[14]

Our third step is to clean the data and obtain firm identifiers that we will use to merge the DEF 14A filings to CRSP, Compustat, and other databases. This cleaning and merging involves five steps:

1. DEF 14A filings have CIK as a firm identifier. We first use the WRDS SEC Analytics Suite GVKEY-CIK linking file to obtain each firm's GVKEY. We follow WRDS' suggestion and only keep GVKEY-CIK matches in which the validation flag is either a 2 or 3. Per WRDS, *"2. - represents CIK-CUSIP links for companies that have a valid 8-digit CUSIP and matching company name in the CUSIP Master dataset. 3. - is for CIK-CUSIP links with 9-digit CUSIPs that were found in SEC filings that match the CUSIPs and respective company names in the CUSIP bureau dataset."* This merge reduces the sample to 168,943 DEF 14A filings.
2. We use the PERMNO-GVKEY linking file from the CRSP-Compustat merged database to obtain each firm's PERMNO, reducing the sample size to 136,165 filings.
3. In a handful of cases, a single GVKEY is mapped to more than one CIK. To obtain a unique GVKEY-fiscal year pair for these observations, we keep the GVKEY-CIK pair where the CIK matches the header (most recent) CIK reported in Compustat. This step reduces the sample size to 133,940 filings.

[14] For some filings, we are unable to identify the election of directors paragraphs and the keyword search return is empty. In these cases, we treat the observation as not having a classified board.

4. There are also situations where a firm appears to have more than one DEF 14A filing in a fiscal year. We have spot-checked a handful of these cases, and the most common source of this problem is that firms incorrectly file a document, such as a DEFM 14A, as a DEF 14A. These types of errors are usually observable because the filing date of the DEFM 14A (or other document) does not occur around the "normal" proxy statement filing month. For example, a December fiscal year-end firm will typically file its DEF 14A in April or May. If we observe a second DEF 14A filed in September, it is a strong indication that this second filing is not the annual proxy statement. Thus, when a firm has more than one DEF 14A filing during a year, we keep the filing that falls within the +/- 1-month window around the "normal" filing month, which we define as the mode filing month over the years that the firm is in the sample. In a few cases, a firm has no filings that fall in this window during a year. For these cases, we keep the earliest filed DEF 14A, as most DEF 14A filings are filed 7-9 months before the next fiscal year-end. This step reduces the sample size to 130,510 filings.
5. We drop firms with a two-digit SIC code of 67: "Holding & Other Investment Offices". These holdings companies often discuss companies they hold in their DEF 14A filings, and it is very difficult to separate when they are discussing the holdings company's board or the board of one of their holdings. Excluding these firms reduces the sample to 110,511 filings.

IA.1.2. Text processing and machine learning

After we obtain our sample of DEF 14A filings, our fourth step is to remove from the text the same set of stop words (except "i") used in Frankel, Jennings, and Lee (2022) and numbers with more than one digit because these numbers are unrelated to classified boards and more likely to capture years, page numbers, and director ages. We further reduce each word to its stem using the Porter stemmer technique so that, for example, "elects", "elected", "election", and "electing" all become "elect". We then convert this text into unigrams and bigrams (one- and two-word phrases) that indicate whether the specific phrase appears at least once. We only include one- and two-word phrases that appear in at least 1,000 of the 110,511 observations, resulting in a corpus of 2,287 variables that we use as inputs into the RF Classifier algorithm. After we obtain all the related text, we merge it with the ISS database for which we know the classified board status of firms. We have 39,998 DEF 14A filings matched to ISS. Among these observations, we use 80% of them as a training sample and the remaining 20% as an out-of-sample test dataset.

Our final step is to determine the RF Classifier model parameters and make the out-of-sample prediction using the 20% reserved test sample. To obtain model parameters, we run a short simulation to optimize the model for in-sample performance. We consider the following key parameters in the RF Classifier algorithm. First, we determine the number of trees in the forest (number of estimators) and the maximum number of levels in each tree (maximum depth). On the one hand, the algorithm considers more information from the training dataset when more trees are used in the algorithm and there are more splits in each tree, which could lead to a better prediction (i.e., less errors). On the other hand, if we set the number of trees and levels in each tree too high, it could require unnecessary computational power without improving the model prediction. We also require a minimum number of samples to split a node (minimum sample split) and a minimum number of samples at each leaf node (minimum sample leaf), which determines the number of nodes and the depth of each decision tree. The algorithm is more precise when the minimum sample split and leaf are smaller. Last, we consider the maximum number of predictors we use for each individual tree.

We seed the training sample with the following parameters: the number of trees in the forest (starting from 10 to 1,000, with 110 as the interval), the maximum number of levels in each tree (starting from 10 to 110, with 10 as the interval), the minimum number of samples required to split a node (2, 5, 10, 15, 20, 25), and the minimum number of samples required at each leaf node (1, 2, 4, 8, 16, 32, 64). The maximum number of predictors is either the square root of all predictors or the logarithm base 2 of the number of predictors. The RF Classifier algorithm runs through all combinations of these parameters and then determines the best parameters given the best accuracy using cross-validation techniques in the training sample. The results from our simulations indicate the optimal number of trees in the forest is 780, and we require at least two samples to split a node and a minimum of one observation on each leaf node. The optimal number of levels in each tree is determined by each individual tree.[15] The optimal number of predictors we use for each tree is the logarithm of the total number of predictors to the base 2.[16] We then use the "best RF" to predict the classified board status for the out-of-sample test dataset and evaluate the algorithm's success. We then extend the predictions to the universe of firms with DEF 14A filings.

IA.1.3. Validating our classified board predictions and manually inspecting the dataset

Given that our application of the RF Classifier is a new approach to predicting classified board status, it is important to validate our measure and assess the out-of-sample prediction accuracy. We use three different approaches to assess the validity of our classified board predictions and make corrections. First, we test the out-of-sample error rate. As mentioned earlier, 20% of the ISS sample is reserved as the testing sample. We treat observations with a predicted probability of more than 50% as having a classified board. Overall, the accuracy from these predictions is quite high. For all the observations that have classified board information from the ISS Governance database, the predictions have an accuracy rate of around 99.34% (0.32% false negatives, where our classification algorithm assigns a firm as not having a classified board but ISS does, and 0.34% false positives, where our algorithm assigns a firm as having a classified board but ISS does not). Not surprisingly, the in-sample prediction accuracy is extremely high at 99.85%, with all but five of the inaccurate predictions coming from false negatives. Our out-of-sample accuracy rate is also high at 97.30% (1.54% false negatives and 1.16% false positives).

To better illustrate the power of the RF Classifier, we next compare our approach to a traditional keyword search method (e.g., Karakaş and Moseni, 2021). For example, if we consider the keyword searches around "class" and "term" as described in our second estimation step in the prior section and assign a classified board to any firm with these keywords, the error rate is 22.24% (21.26 % false positives and 0.98% false negatives). Manual investigation indicates the keyword

[15] The average level of depth in our testing sample is 84, and the minimum (maximum) level of depth is 54 (129).
[16] In untabulated results, we follow Frankel et al. (2022) and use 5,000 trees. The model gives almost identical out-of-sample error rates, suggesting that our optimal parameters are sufficient to determine a firm's classified board status.

search for “class” drives a significant number of false positives, misidentifying “classes of directors” with “classes of securities”. If we refine this classification by requiring the word “class” be followed by “i”, “ii”, “iii”, “1”, “2”, or “3” or preceded by “two” or “three”, the error rate decreases to 8.68% (6.68% false positives and 2.0% false negatives). Modifying the keyword search this way highlights the shortcomings of keyword searches – making the search narrower to reduce false positives increases the number of false negatives.

While these refinements help reduce the keyword search error rate, they quickly lose parsimony, becoming much more ad hoc and less generalizable as a method. Conversely, the RF Classifier has the advantage of both needing far fewer restrictive refinements and producing a substantially lower error rate than the keyword search method. In particular, using the original stacked keyword search text that we outline in the second estimation step in sub-section IA.1 with the keywords “class” (without any refinements) and “term”, the RF Classifier produces an error rate for the training sample of 1.23% (0.08% false positives and 1.15% false negatives) and an out-of-sample error rate of 3.28% (1.42% false positives and 1.86% false negatives). In other words, the RF Classifier for the combined training and out-of-sample datasets reduces the error rate of the refined keyword search algorithm by 81%.

Finally, we manually check all instances when our predictions do not match those in the ISS database and when S&P and non-S&P 1500 firms change to or from having a classified board. We also remove invalid observations and keep one observation for each GVKEY-FYEAR, reducing the sample to 110,176 observations. With respect to discrepancies between our predictions and the ISS database, they appear to arise from a few main sources. One source is that firms occasionally file the wrong document. For example, a firm may mistakenly file a DEF 14A, but the correct filing should have been a DEFM 14A, as it relates to a merger not the annual proxy statement. This situation occurs rarely. A second source of inaccuracy is that firms sometimes file a proxy statement proposing to change from a single class to a classified board (or vice versa), but the proposal fails. Discrepancies also arise in a few circumstances due to the imperfect matching of firms across the databases.

The final source of inaccuracy is inconsistent coding when distinguishing between when (i) a shareholders vote to (de)classify a firm's board and (ii) the (de)classification is fully implemented; this issue is also present in the ISS database. For example, firms typically phase out their classified board over the few years after the proposal to declassify is approved. This discrepancy in the timing between the firm approving and fully implementing the change in classified board has implications for different types of analyses. For instance, when examining the economic determinants of the decision to declassify a board, the relevant date is when shareholders vote to pass the resolution to declassify, not when the board is fully declassified. In contrast, when examining the relation between firm outcomes, such as M&A decisions or shareholder value, the relevant period is when all directors can be replaced at the annual meeting (i.e., a fully declassified board) that creates disciplining incentives. Consequently, we create two different "classified board" indicator variables that distinguish between when shareholders vote to approve to (de)classify their board and when board (de)classification is fully implemented.

IA.2. Additional Results

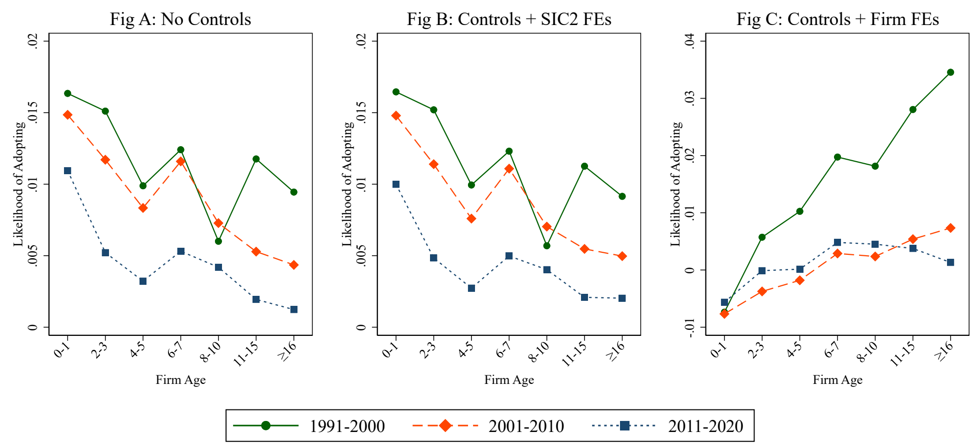
Figure IA.2.1
Likelihood of Adopting Classified Boards by Firm Age, Decade, and IPO Cohort

Panel A (B) shows the likelihood of a firm adopting a classified board over time by firm age group and decade (IPO cohort). The figures plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of an indicator variable equal to one if a firm adopts a classified board in year t and zero otherwise (*Adopt*) on controls, where regressions are estimated separately for each decade in Panel A (IPO cohort in Panel B):

$$Adopt_{it} = \sum_{a=0}^{\geq 16} \omega_a Age_{it} + \Gamma X_{it} + \eta_k + \gamma_i + \varepsilon_{it}.$$

Age_{it} equals one if firm age is in age group a, and zero otherwise. X_{it} are firm-level characteristics, defined in Appendix B, that include $Ln(Assets_{t\text{-}1})$, IO_t, $Delaware_t$, and $S\&P\ 1500_t$. η_k and γ_i are two-digit SIC industry and firm fixed effects, respectively.

Panel A: Likelihood of Adopting CB by Firm Age and Decade



Panel B: Likelihood of Adopting CB by Firm Age and IPO Cohort

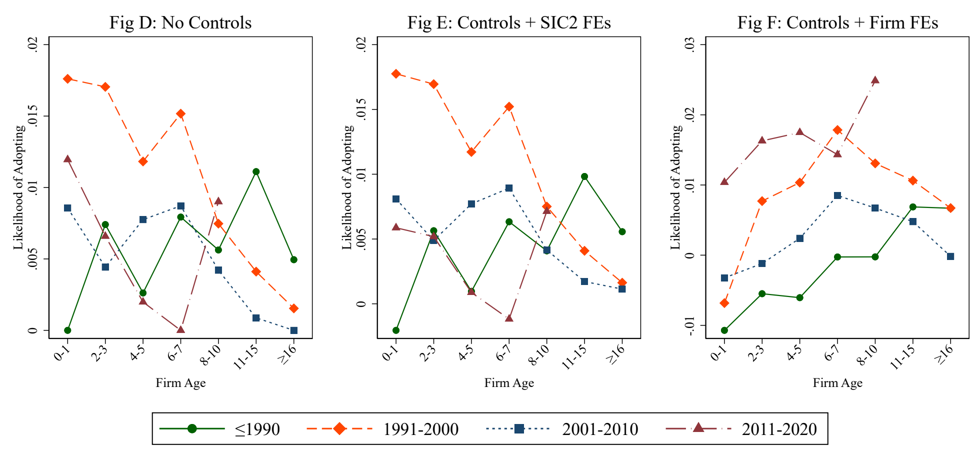


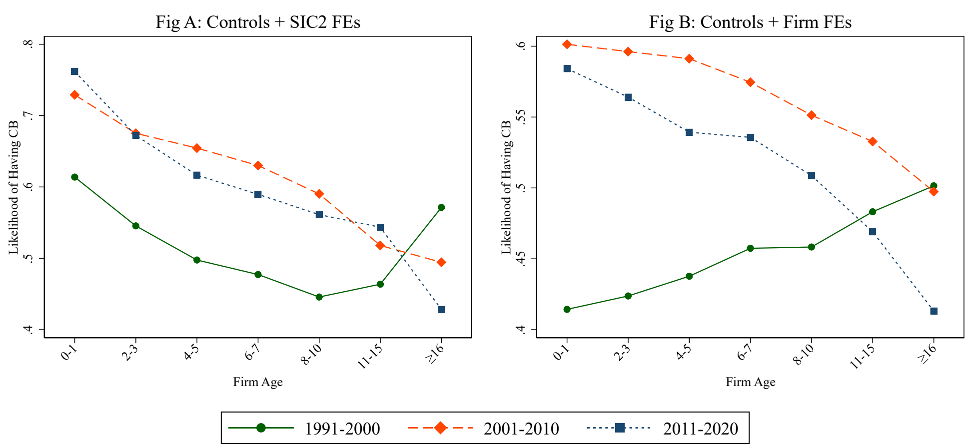
Figure IA.2.2
Use of Classified Boards by Firm Age, Decade, and IPO Cohort: Additional Controls

Panel A (B) shows the fraction of firms with a classified board by firm age group and decade (IPO cohort). The figures plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of the classified board indicator (*CB*) on controls, where regressions are estimated separately for each decade in Panel A (IPO cohort in Panel B):

$$CB_{it} = \sum\nolimits_{a=0}^{\geq 16} \omega_a Age_{it} + \Gamma X_{it} + \eta_k + \gamma_i + \varepsilon_{it}.$$

Age_{it} equals one if firm age is in age group a, and zero otherwise. X_{it} are firm-level characteristics defined in Appendix B and Section 4.1, that include $Ln(Assets_{t-1})$, $Ln(Assets_{t-1})^2$, $Ln(Assets_{t-1})^3$, IO_t, $Delaware_t$, $S\&P\ 1500_t$, $Tobin's\ Q_t$, $OpROA_t$, $BookLev_t$, $Capex_t$, $R\&D_t$, $Ln(Turnover_t)$, $Ln(RetVol_t)$, and $Ln(\#Analysts_t)$. η_k and γ_i are two-digit SIC industry and firm fixed effects, respectively.

Panel A: Use of CB by Firm Age and Decade



Panel B: Use of CB by Firm Age and IPO Cohort

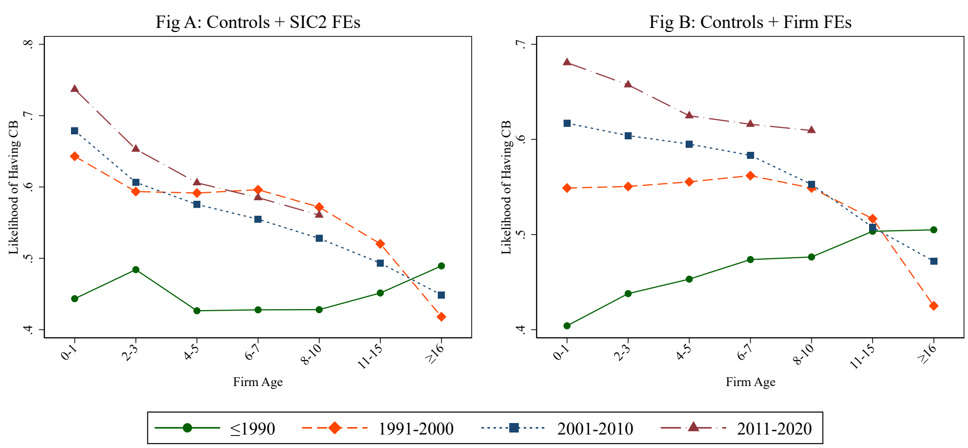


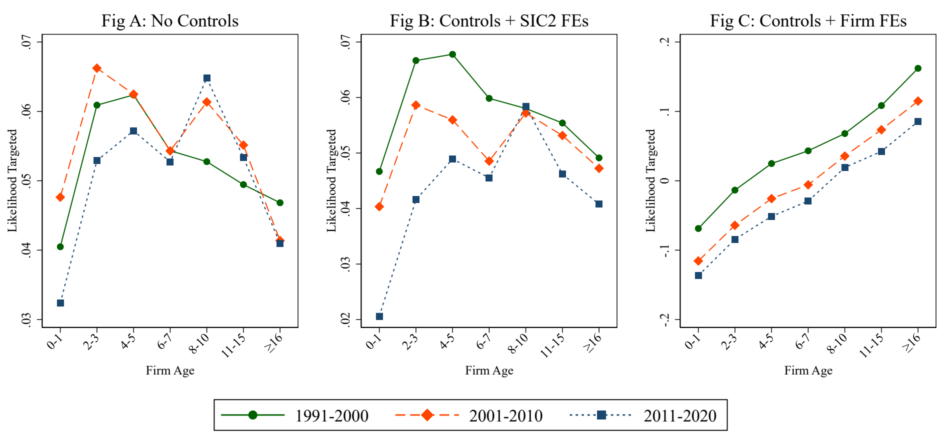
Figure IA.2.3
Likelihood of Being M&A Target by Firm Age, Decade, and IPO Cohort

Panel A (B) shows the likelihood that a firm is targeted for a takeover over time by firm age group and decade (IPO cohort). M&A data are from SDC. Firms are considered targeted if they receive a bid from a potential acquirer that owns less than 50% of the firm before the bid and seeks to own more than 50% of the firm after the deal is completed. The figures plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of the targeted for takeover indicator (*Target*) on controls, where regressions are estimated separately for each decade Panel A (IPO cohort in Panel B):

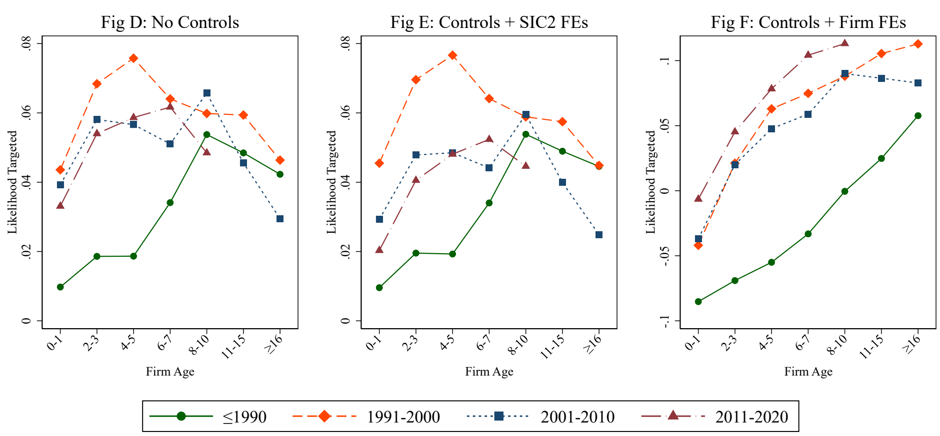
$$Target_{it} = \sum_{a=0}^{\geq 16} \omega_a Age_{it} + \Gamma X_{it} + \eta_k + \gamma_i + \varepsilon_{it}.$$

Age_{it} equals one if firm age is in age group *a*, and zero otherwise. X_{it} are firm-level characteristics, defined in Appendix B, that include *Ln*(*Assets*$_{t-1}$), *IO*$_t$, *Delaware*$_t$, and *S&P 1500*$_t$. η_k and γ_i are two-digit SIC industry and firm fixed effects, respectively.

Panel A: Likelihood of being Targeted by Firm Age and Decade



Panel B: Likelihood of being Targeted by Firm Age and IPO Cohort



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