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Keywords: Corporate governance, Takeover defenses, Classified (staggered) boards, Life

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

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THIRTY YEARS OF CHANGE: THE EVOLUTION OF CLASSIFIED BOARDS

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Abstract

Based on a comprehensive data set of classified (staggered) boards covering nearly all U.S. public firms from 1991 to 2020, we show that contrary to conventional wisdom, the use of classified boards remains widespread. Moreover, classified board usage over a firm's life cycle depends significantly on the decade the firm matured or year it went public. While classified boards were rarely removed in the 1990s, firms became more likely to declassify as they matured during the following decades. Decreased collective action costs and increased innovation-related investments, institutional ownership, and scrutiny of governance contributed to this more dynamic adjustment.

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As one of the most powerful corporate takeover defenses, classified (or staggered) boards have faced intense scrutiny.[1] While prior studies provide conflicting evidence on whether the costs or benefits of classified boards dominate, recent work suggests that some of these mixed findings may be explained by the life-cycle effects of takeover defenses, whereby the costs of these defenses start to outweigh their benefits as firms mature (Johnson, Karpoff, and Yi (2022)). Despite this important insight, there is little direct evidence on how and why firms use classified boards over their life cycle and whether such patterns have changed over time. This latter aspect is crucial, as fundamental changes to the corporate governance landscape in recent decades (e.g., Madden (2011), Kastiel and Nili (2021)) may have altered the life-cycle dynamics of classified board usage. Such changes include greater scrutiny and awareness of governance practices following major corporate scandals in the early 2000s, increased ownership stakes by passive institutional investors and hedge fund activists, and improvements in information transparency and accountability. Our paper aims to fill this gap by investigating the following research questions: Have the life-cycle dynamics of classified board usage changed over time, what key factors have contributed to these changes, and do changes in these life-cycle dynamics have implications for firm value.

The prevailing narrative is that classified board usage has been declining among S&P 1500 index firms (e.g., Cremers, Litov, and Sepe (2017), Karakas and Mohseni (2021)), leading some researchers to conclude that "corporate America is giving up the [classified] board" (Subramanian (2007)) and classified boards "are on their way toward endangered-species status" (Strine (2014, p. 497)). Amidst this apparent decline, however, the proportion of firms going public with classified boards has been increasing (e.g., Field and Karpoff (2002), Field and Lowry (2022)). Moreover, Johnson, Karpoff, and Yi (2022) show that although the costs of having a classified board exceed the benefits as firms age, firms rarely adjust this defense, resulting in a value reversal pattern whereby a positive relation between valuations and classified boards turns negative as firms

[1] Under a classified board structure, directors are divided into classes and serve staggered terms, with only one class standing for reelection each year. This board structure protects firms from takeover attempts, as potential bidders are forced to win successive director elections to gain board control. Proponents argue that classified boards facilitate longer-term strategies and relationships, while critics maintain that they entrench managers and undermine shareholder interests. For surveys of this literature, see Straska and Waller (2014) and Karpoff and Wittry (2024).

mature. With a few exceptions,[2] most prior work relies on specific types of firms or limited sample periods, and thus the important questions of how and why life-cycle patterns in the use of classified boards may have changed over time remain unexplored. We attempt to fill this void by examining a more comprehensive sample of firms over an extended period.

To examine the evolution of classified board usage during a firm's life cycle and over time, it is necessary to have a data set that tracks firms throughout their life span. The most widely used takeover defense data come from the Institutional Shareholder Services (ISS) governance database (also known as the RiskMetrics and Investor Responsibility Research Center (IRRC) database). However, this database is limited to more mature and well-established firms in the S&P 1500 and does not include data for the years before or after a firm is added or removed from the index. As a result, data from ISS do not capture a firm's life cycle, nor do they reflect the governance decisions of firms not in the S&P 1500. Yet understanding classified board usage by firms in the years before they were added to the S&P 1500, as well as by the firms that are never included in the index, is essential for understanding the full evolution of corporate governance structures over time, as both sets of firms play an important role in shaping market dynamics and the economy through their influence on supply chains, competition, consumer behavior, and job creation.

We construct a new data set on classified boards for almost all U.S. public firms from 1991 to 2020. We generate this data set by combining a machine learning technique–the Random Forests (RF) Classifier–with textual analysis and manual inspection. Thus, while our paper focuses on how and why the use of classified boards over a firm's life cycle has changed over time, we also provide a framework for both expanding existing databases using innovations in machine learning and making these data available to others. Our novel classified board data set has about three times the number of firm-year observations compared to commercial databases.

Using this dataset, we document several new findings. First, we show that contrary to the prevailing narrative, classified boards are not going extinct—rather, this trend holds only among

[2] Some prior work considers the use of classified boards in firms outside the S&P 1500 using hand-collected data (e.g., Johnson, Karpoff, and Yi (2015, 2022), Field and Lowry (2022)). Although these papers contribute to our understanding of governance structures in these firms, we take a different approach and focus on the evolution of classified board usage over a firm's life cycle and factors driving changes in this usage pattern over time.

firms in the ISS database. In particular, we show that while the fraction of S&P 1500 firms with a classified board decreased from 58% in the early 1990s to 31% in 2020, the fraction of firms outside the index with a classified board increased from 42% to 52% over the same period.[3] These findings indicate that trends observed using databases like ISS do not capture most firms' use of classified boards over time.

Second, and central to the focus of our study, we find that the use of classified boards across a firm's life cycle varies significantly over time. In the 1990s, classified board usage declined only slightly as firms aged. This pattern is consistent with the view that takeover defenses tend to be sticky and infrequently adjusted by firms (e.g., Cremers and Ferrell (2014)). Between 2001 and 2010, however, 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% (33%) of the youngest (most mature) firms had a classified board. Similarly, when we split the sample into initial public offering (IPO) cohorts, the earliest cohort of IPO firms in our sample was more likely to retain a classified board as they aged, while the most recent cohort was far less likely to have a classified board as they matured. We observe similar decade and IPO cohort effects when we examine declassification rates. These results highlight substantial differences over the past 30 years in how firms use classified boards over their life cycles.

Third, we investigate what factors may have contributed to these changing life-cycle trends in classified board usage. Theory predicts that in the absence of frictions, value-maximizing firms should adjust their use of classified boards according to results of a cost-benefit analysis. Classified boards can be value-enhancing for firms that tend to rely on long-term projects with greater information asymmetry because a classified board may help protect these firms and their managers from markets and external investors that cannot directly observe the value of these initiatives. However, classified boards can be costly if protecting managers increases agency problems.

[3] The trend difference is even more striking for firms in the S&P 500, as the fraction of these firms with a classified board dropped from 60% in the early 1990s to only 12% by 2020. The sharp decrease in the use of classified boards among S&P 500 firms coincided with Harvard Law School's Shareholder Rights Project, which pushed for many of these firms to declassify their boards.

Moreover, high collective action costs may prevent shareholders from removing classified boards even when the costs outweigh the benefits. In sum, differences in investor horizons and objectives, heterogeneous shareholder beliefs, and coordination problems may prevent firms from optimally adjusting takeover defenses over their life cycle (e.g., Kahan and Klausner (1996), Hannes (2006), Johnson, Karpoff, and Yi (2022)).

Motivated by these arguments, we explore how the costs and benefits associated with classified boards have evolved. First, based on prior work, we examine the intensity of young firms' investments in innovation-driven activities over the last 30 years. These investments, such as research and development (R&D) and intangible assets, create information asymmetries that may lead classified boards to add value. We find that young firms have steadily increased their investments in R&D and intangible assets over the past three decades, consistent with Field and Lowry (2022). This trend is consistent with our evidence that young firms have increasingly adopted classified boards. Moreover, not only have young firms intensified their investments in R&D and intangibles, but they have reduced them more rapidly as they age. This change mirrors how firms have adapted their use of classified boards and supports the theoretical prediction that the costs of this defense exceed its benefits as firms mature (Johnson, Karpoff, and Yi (2022)).

Second, we investigate how collective action costs associated with declassifying boards have changed over time by focusing on trends in three measures that aim to capture differences in shareholders' objectives, horizons, and ability to coordinate during the firm's life cycle: (i) passive institutional investor ownership, as passive index funds displeased with a firm's governance practices cannot exit their positions (i.e., "Wall Street Walk") and thus must engage with management to advocate for changes, (ii) bid-ask spreads, which proxy for investors' information heterogeneity, and (iii) the likelihood of a firm being targeted by a hedge fund or receiving a shareholder proposal to declassify. The trends that we observe in these outcomes are consistent with those in classified board usage: passive institutional ownership increases as firms age, with this increase being more pronounced in later decades; bid-ask spreads have decreased over time, reaching a low in the most recent decade and maintaining this lower level across a firm's life cycle;

and the likelihood that firms are targeted by hedge funds or receive a shareholder proposal to declassify increases as they age, especially in the most recent decade.

Further supportive of a shift in sentiment against classified boards and increased shareholder involvement after major corporate scandals in the early 2000s, over the last decade the relation between having a classified board and institutional investor ownership turned negative for mature firms. Similarly, mature firms that are larger or that are in the S&P 1500 became more likely to declassify their boards only during the last decade, whereas this effect is absent among young firms. In a matched-sample difference-in-differences analysis, we show that firms, especially older firms, began declassifying their boards after being added to the S&P 1500 only during the most recent decade.

We next explore several alternative explanations, none of which can explain our findings. First, we show that trends in the importance of stakeholder relationships, which benefit from takeover protection, are inconsistent with the life-cycle trends in classified boards. Second, we find that changes in the market for corporate control do not drive the patterns in classified boards. While takeover activity has changed, these changes appear across all firm-age groups. Third, we explore whether changes in firm characteristics can explain our results. For example, over the past 30 years, firms have grown larger and invested less in tangible assets. However, even after controlling for a comprehensive set of time-varying firm characteristics, industry fixed effects, and firm fixed effects where trends are derived from within-firm variation, the patterns that we observe in classified board usage persist. Fourth, we show that survivorship bias cannot explain our results. We repeat our analyses using a subsample of firms that survive at least 10 years each decade and find that the life-cycle patterns remain. Finally, we show that firm age does not simply proxy for firm size, but rather is a distinct proxy for a firm's life cycle. When we examine the life-cycle patterns in classified boards over time and across size groups instead of age, we find very different patterns, indicating that firm age captures the net effect of the costs and benefits of classified boards over the life cycle.

In summary, our findings suggest that evolving costs and benefits associated with having a classified board, shifts in the U.S. corporate governance system, and reduced collective action costs have contributed to firms declassifying their boards more quickly as they mature. However, two important caveats should be noted. First, without a valid instrumental variable or natural experiment for each mechanism, we cannot establish causality between trends in classified boards and trends in related outcomes. Our results should therefore be interpreted with this limitation in mind. Second, we present and examine a relatively comprehensive view of classified boards. Due to this complexity as well as the inherent noise in empirical data, not all of our results always yield statistically significant inferences. Nevertheless, the collective evidence supports our proposed narrative.

The last part of our paper explores the relation between classified boards and firm value. As Johnson, Karpoff, and Yi (2022) show, high collective action costs and free-riding problems among shareholders are frictions that hinder firms from dynamically adjusting their use of classified boards, resulting in a positive association between firm value and defenses for young firms and a negative association for mature firms. Our finding that the use of classified boards has become less sticky over time has implications for this value reversal pattern. Specifically, if firms dynamically adjust their defenses as they become more costly, this value reversal effect over the life cycle should diminish. Our analysis reveals that in the 1990s and 2000s, classified boards added value to newly public firms but decreased value among older firms. This pattern then disappeared in the 2010s, when firms became more likely to declassify as they aged. These results imply that as governance scrutiny increased and the cost of collective action decreased, the frictions that had historically impeded firms from optimally adjusting their classified boards over their life cycle lessened by the 2010s.

The remainder of the paper is organized as follows. Section I discusses how our paper relates to the existing literature. Section II describes our classified board data. Section III documents life-cycle trends in classified board usage. Section IV investigates potential mechanisms explaining these trends. Section V examines the implications of these trends for firm value. Finally, Section VI concludes.

I. Related Literature

This paper contributes to several strands of literature. First, our finding that an increasing number of non-S&P 1500 firms have been using classified boards over time challenges the widespread belief that firms have significantly reduced their use of classified boards since the 1990s. Prior to our study, most extant evidence of a declining trend in classified boards came solely from S&P 1500 firms (e.g., Ganor (2008), Cremers, Litov, and Sepe (2017)). Although a few studies provide insights into how IPO firms use classified boards (e.g., Johnson, Karpoff, and Yi (2015, 2022), Field and Lowry (2022)), our understanding of how the majority of firms use them remains limited. Our results suggest that contrary to conventional wisdom, most U.S. public firms continue to include classified boards in their governance structures.

Second, our findings on the evolution of classified board usage throughout a firm's life cycle and the underlying reasons for these changes offer fresh insights into understanding governance structures across different types of firms and time periods. These results not only expand on the literature that challenges the notion of a "one-size-fits-all" approach to takeover defenses, but also provide a much-needed explanation for the observed time-varying effects of classified board usage across firms, addressing a gap in the literature that has often treated classified boards as static. Johnson, Karpoff, and Yi (2022) show that from 1997 to 2011, takeover defenses were rarely removed as firms aged, which they attribute to high collective action costs and free-riding problems among shareholders. Field and Lowry (2022) document that the percentage of firms that go public with a classified board has increased over time. Meanwhile, prior work shows that the use of classified boards by mature firms in the S&P 1500 has been mostly declining since the mid-2000s (e.g., Cremers, Litov, and Sepe (2017), Karakas and Mohseni (2021), Field and Lowry (2022)), with shareholder activism contributing to this trend (Ge, Tanlu, and Zhang (2016)).

However, except for Johnson, Karpoff, and Yi (2022), most studies do not consider firms' use of classified boards over their life cycle. We add to this literature by providing direct evidence on the evolution of classified board usage across firms' life cycles and over time. We document that classified boards have become increasingly less sticky over the past three decades, adjusted more dynamically as firms age. Our investigation of the costs and benefits of classified boards shows that their value has risen among young firms due to their increased investment in innovation-related activities, which helps explain the growing adoption of classified boards among such firms. In addition, we document increased investor attention to governance, reduced costs associated with removing classified boards, and a rise in shareholder activism over time, potentially explaining the decline in classified board stickiness in recent decades.

Third, our paper relates to the literature examining classified boards and firm valuations. The more dynamic adjustments to this board structure over firms' life cycles in recent decades have implications for the value reversal hypothesis proposed by Johnson, Karpoff, and Yi (2022). As discussed earlier, we add new insights to this literature by showing that this reversal effect has declined 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 and the subsample of firms studied.

Fourth, our paper relates to a growing finance literature studying the importance of cohort effects. Many papers examine how belonging to a cohort 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 et al. (2017), Parker et al. (2022)), employment outcomes and managerial styles (Oyer (2008), Schoar and Zuo (2017), Law and Zuo (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 and board structures depending on the prevailing corporate governance environment during the decade the firms are aging or at the time of their IPO.

Lastly, we make a methodological contribution by demonstrating how machine learning can be used to construct new data sets 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 et al. (2021), Li et al. (2021)), it has been used primarily to measure latent variables (e.g., risk premiums, culture) and to predict 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.

II. Data and Methodology

A. Data Sources

We construct our base sample from the Center of Research in Security Prices (CRSP)-Compustat merged database over the 30 years 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 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. Only 28.6% of firms in our sample are in the S&P 1500 index.

As inputs to 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.

B. Collecting Classified Board Data from EDGAR Filings

B.1. Overview of the RF Classifier

The RF Classifier is a supervised machine learning algorithm used in modeling predictions and built on 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, the RF Classifier has three main advantages. First, the RF Classifier is based on the bagging algorithm and uses an ensemble learning technique. Intuitively, the 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 features at once and offers only one path, the RF Classifier creates multiple trees with random features, increasing efficiency and making it easier to handle large data sets. Finally, the 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 fields of science, economics, and business. For example, the 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 3-D 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 the RF Classifier in econometrics, and Bajari et al. (2015) use the RF Classifier to estimate demand functions. More recently, Frankel, Jennings, and Lee (2022) show that the RF Classifier captures disclosure sentiment better than alternative machine learning techniques, and Miric, Jia, and Huang (2023) find that the RF Classifier is the best-performing machine learning classifier to identify artificial intelligence technologies in patents.

B.2. Estimation Steps and Machine Learning Prediction

A contribution 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 Section I in the Internet Appendix.[4] 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.

In the first step, we obtain the relevant text in the DEF 14A filings discussing the election of directors. We start by requiring that a DEF 14A 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 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. In Section II of the Internet Appendix, we include an example of a proxy statement with this paragraph. Using this approach, we identify these paragraphs for 85.3% of the DEF 14A filings.

Because we cannot capture all potential variants of "election of directors" mentioned in the DEF 14As, in a second step, we conduct two specific keyword searches indicating the presence of a classified board. We search the DEF 14A filings for variations of the words "class" and "term" and keep the 10 words before and after each instance. We require the words "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 in which "class" refers to share classes. For "term," we also require the phrase "[number] [optional non word character] year" or "stagger" to appear within these 10 words. This criterion is designed to capture instances in which 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 in the "election of directors" paragraphs described earlier. We combine all the paragraphs and texts into one corpus for each CIK-FDATE pair.

[4] The Internet Appendix is available in the online version of the article on the *Journal of Finance* website.

In a third step, we clean the data of 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"), which reduces the sample to 110,511 firm-year observations.

The fourth step removes stop words (except "i") and numbers unrelated to classified boards (e.g., years 1940 to 2020 and ages 20-99) from the text and reduces 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. We use 80% of these observations as our training sample and the remaining 20% as the out-of-sample test data set.

In our final step, we 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 tree. The RF Classifier algorithm cycles through several combinations of the parameter values and determines the best parameters with the best accuracy using cross-validation techniques in the training sample. We use the "best RF" to predict classified board status for the out-of-sample test data set 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 specifies which variables have the most predictive power. To calculate the variable importance of each predictor *i*, the 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 IA.1, Panel A in the Internet Appendix 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 S&P and non-S&P 1500 firms. This possibility would create 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 IA.1, Panel B shows that the fraction of S&P 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, which indicates that both groups use nearly identical wording.[5]

B.3. Validating our Classified Board Predictions and Manually Inspecting the Data Set

Given that our application of the RF Classifier is a new approach to predicting a classified board, validating our measure and assessing its 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; we provide further details 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-

[5] 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 non-S&P 1500 firms in 2017. There were 1,118 non-S&P 1500 firms in 2017, but only 228 were in the test sample. We find only eight differences among these 228 observations.

sample prediction accuracy is also very high at 97.3% (with 1.5% false negatives, where our classification 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 that 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.

Third, we manually check all instances in which our predictions do not match those in the ISS database and in which any firm in our sample changes its classified board status. Discrepancies between our predictions and ISS arise from a few main sources. One 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 of discrepancy 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 changes over the few years after the proposal is approved, and these timing differences matter depending on the analysis. For example, when examining 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 relationship between policy 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. We create two classified board indicator variables that distinguish when firms vote to (de)classify their board and when board (de)classification is fully implemented. For our analyses, we use the indicator based on the voting date.

C. 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 these data from the electronic filings). If a firm's classified board status is the same in these first and last years, we assume that 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. We hand-collected classified board data for an additional 7,614 firms before EDGAR filings were available, increasing the sample size by 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 that 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 is 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.[6] This additional collection increases our data set by 3,964 firm-year observations.

D. Sample Overview

While we determine the classified board status of all firms using DEF 14A filings, we impose the following requirements for a firm to be included in our analyses: (i) it can be matched to CRSP, (ii) it has valid information for its market value of equity, (iii) its age is nonnegative, and (iv) its SIC code is less than 9100 (i.e., its industry classification is not public administration and is classifiable). These restrictions yield a sample of 137,032 firm-year observations. The Appendix provides definitions for the main variables used in our analyses.

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

[Table I here]

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

III. Trends in Classified Boards

A. Classified Board Usage by Time and Firm Age

In Figure 1, Panel A, we examine trends in how firms use classified boards over time and by firm age. In this and subsequent figures, we tabulate results (i) without controls, (ii) with controls for firm size, institutional ownership, whether the firm is incorporated in Delaware, whether the firm is in the S&P 1500, and two-digit SIC industry fixed effects (similar to Johnson, Karpoff, and Yi (2022)), and (iii) with these firm-level controls as well as firm fixed effects.

[Figure 1 here]

In Panel A1, we plot the fraction of firms with a classified board over time. As can be seen, firms have become less likely to use classified boards over the past two decades. Based on the results without controls, 43.2% of firms had a classified board in 1991 to 1992, and this percentage increased through the 1990s and early 2000s before reaching a peak of 55.5% in 2003 to 2004. However, from then forward, the fraction of firms with a classified board began to decline significantly to 43.9% in 2019 to 2020. Including firm-level controls and industry fixed effects has little effect on the overall trend beyond increasing the steepness of the decline in classified board usage. For example, in the model that controls for industry fixed effects, roughly 55.0% of firms had a classified board in the early 2000s, with this value dropping to 39.2% in 2019 to 2020. Adding firm fixed effects magnifies this trend further, showing that the fraction of firms with a classified board dropped from about 54.0% in the early 1990s to 30.3% in 2019 to 2020.

These initial findings suggest that firms have been progressively less likely to use classified boards since the mid-2000s, consistent with the claim by several leading legal experts that classified boards are becoming rare and are on their way toward endangered-species status (e.g., Strine (2014)). However, before this study, most evidence of a declining trend in classified boards came solely from firms in the ISS database (e.g., Ganor (2008), Cremers, Litov, and Sepe (2017)). In Panel A2, we employ our new data set and the model without controls to examine whether this claim holds for firms outside the S&P 1500.

The figure starts in 1995 to 1996 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 those not included in the indices. While the use of classified boards has declined 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 non-S&P 1500 firms. To illustrate this difference, the percentage of S&P 500 firms with a classified board dropped from 60.0% in 1995 to 1996 to only 12.2% in 2019 to 2020, whereas about 42.4% of non-S&P 1500 firms had a classified board in 1995 to 1996 and 51.8% had this provision in 2019 to 2020. Thus, while classified boards have become rarer among S&P 1500 firms, they remain a common defense for firms outside the index.

In Panel A3, we explore differences in firms' use of classified boards as they progress through different life-cycle stages. We decompose firm age into seven groups based on the years since a firm's IPO: 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, and Yi (2015), Field and Lowry (2022)), whereas this fraction declines steadily as firms mature. Based on the results without controls, 57.7% of firms aged 0-1 use classified boards, but this fraction declines to 48.1% by the time they reach ages 8-10 and to 43.6% for mature firms aged ≥16. This life-cycle pattern is consistent with the benefits associated with classified boards being greatest among younger firms, but the costs becoming more pronounced as firms mature.

B. Trends in Classified Board Usage Over Time by Firm Age

In Figure 1, Panel B, we examine whether classified board usage at different stages of a firm's life cycle has changed over the past three decades by plotting the fraction of firms with a classified board over time by four age groups: 0-2, 3-6, 7-10, and ≥11. Based on the model without controls, Panel B1 shows that the fraction of the youngest firms with a classified board has been increasing since the 1990s, from a low of 37.6% in 1991 to 1992 to a high of 74.1% in 2015 to 2016 and staying at 72.5% in 2019 to 2020 (consistent with Field and Lowry (2022)). This trend is similar for firms aged 3-6 and 7-10 during the 1990s, but the trend mostly plateaus in the early to mid-

2000s. For the most mature firms aged ≥11, a much smaller fraction maintained classified boards over time. For firms publicly traded for more than 10 years, 51.3% had a classified board in 1991 to 1992, and this fraction dropped to 33.5% in 2019 to 2020.

Including firm-level controls and industry fixed effects in Panel B2 does not change the patterns much, whereas Panel B3, 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 53.0%, but this fraction began to decline starting in the early 2000s, reaching a low of 25.0% in 2019 to 2020.

C. Trends in Classified Board Usage by Firm Age, Decade, and IPO Cohort

In Figure 2, we present our key analysis by using our new data set to investigate whether, during the past 30 years, firms have used classified boards differently over their life cycle depending on the decade or their IPO cohort. Panel A examines whether the life-cycle patterns in classified board usage from Figure 1 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 to 2000, 2001 to 2010, and 2011 to 2020. Panel A1 shows that in analyses without controls, the use of classified boards only declines slightly as firms age from 0-15 during the 1991 to 2000 decade before increasing for the most mature firms aged ≥16. This result is generally 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 to 2020 decade, 72.8% of firms aged 0-1 had a classified board, and this fraction decreased to 33.0% for firms aged ≥16.

[Figure 2 here]

Panel A2 shows that the patterns are similar when controlling for firm-level characteristics and industry fixed effects, albeit with a much smaller increase for the most mature firms during the 1991 to 2000 decade. However, Panel A3, which controls for firm fixed effects, shows increased classified board usage as firms aged between 1991 and 2000. Conversely, during the 2000 to 2010 decade, 58.4% of firms aged 0-1 had a classified board, and this fraction dropped to 48.3% for firms aged ≥16. The decline is even more pronounced during the 2011 to 2020 decade, with 57.0% (39.9%) of the youngest (most mature) firms having a classified board.

In Panel B, we plot the fraction of firms with a classified board across the life cycle conditional on their IPO cohort. We break firms into four groups based on their IPO year: ≤1990, 1991 to 2000, 2001 to 2010, and 2011 to 2020. Focusing on the models without controls, we note two key takeaways from Panel B1. First, the fraction of firms aged 0-1 with a classified board is sequentially higher across each decade, with values of 33.5%, 52.1%, 63.7%, and 73.1% for firms with IPOs during the ≤1990, 1991to 2000, 2001 to 2010, and 2011 to 2020 periods, respectively. Second, during the earliest (last) two decades, firms declassify their boards slower (faster) as they mature. By age 8-10, 40.1% and 53.8% of firms with an IPO between ≤1990 and 1991 to 2000, respectively, still had a classified board, while the values dropped to 50.9% and 48.0% for firms with IPOs between 2000 to 2010 and 2011 to 2020, 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 classified board usage by young firms is driven by sample composition. However, the panel continues to show steeper declines in how classified boards are used over a firm's life cycle across the more recent IPO cohorts. Including firm fixed effects mutes the declines across the decades, but Panel B3 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]

[7] Our data set begins in 1991, so 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 are incomplete, we interpret the trends (and estimates from later analyses) for this IPO cohort with caution.

While Figure 2 indicates that there have been changes in how classified boards are used by different age groups, depending on their decade and IPO cohorts, it does not show whether these changes are statistically significant. Therefore, using the models with controls and firm fixed effects, Table II examines whether firms adjust their classified boards over their life cycle relative to the youngest firms aged 0-1 significantly differently by decade and IPO cohort. Column (1) includes all firms over the full sample, columns (2) to (4) separate firms by decade, and columns (5) to (8) group firms by IPO cohort. Column (1) shows that, over the full sample, firms make minimal changes in their use of classified boards until they are aged ≥8. Specifically, although the coefficients on the 2-3, 4-5, and 6-7 age dummies are positive (only age group 2-3 is statistically significant), the economic magnitudes are small at less than one percentage point. Conversely, the coefficients on the 8-10, 11-15, and ≥16 age dummies are -1.1%, -2.9%, and -8.6%, respectively, and statistically significant, indicating that mature firms are less likely to have classified boards.

[Table II here]

Columns (2) to (8) confirm that decade and IPO cohort effects significantly change how firms use classified boards over their life cycles. Consistent with Figure 2, Panels A3 and B3, columns (2) and (5) show that during the 1990s or for firms with an IPO prior to 1991, these firms did not declassify as they aged. Rather, the likelihood of having a classified board increases significantly relative to firms' IPO years 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 declines quickly as firms age. Comparing the results across columns also reveals dramatic coefficient differences for the same age groups, indicating decade and IPO cohort-specific age effects. For example, coefficients in age group 2-3 decline monotonically from the earliest to the latest decade and IPO cohort, switching from significantly positive to significantly negative.

D. Trends in Board Declassification by Firm Age, Decade, and IPO Cohort

In Figure 3, we analyze the trends in how firms declassify their boards over their life cycle by decade and IPO cohort. For this analysis, we limit the sample to firms with 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.

[Figure 3 here]

In Figure 3, Panel A, we examine life-cycle effects on the rate of board declassification by decade. Based on the model without controls, Panel A1 shows that, across age groups, the rate that firms declassified their boards during the 1991 to 2000 decade remained flat at around 0.6% to 1.1% per year. Conversely, board declassification rates rose during the 2001 to 2010 decade 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 2011 to 2020 decade, the rate of board declassification was generally higher for all firms aged ≥2 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, Panel A3 shows that the likelihood of a firm declassifying its board increases as it ages across all three decades, although, the increase for the 1991 to 2000 decade was less steep when compared to the following two decades.[8]

Panel B examines life-cycle effects on board declassification rates by IPO cohort. In models without controls, Panel B1 shows that firms aged 0-1 and 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 the 2001 to 2010 period continue to declassify faster than similarly aged firms with IPOs from 1991 to 2000, while the declassification rates of firms going public in the most recent

[8] Johnson, Karpoff, and Yi (2022) report that firms rarely removed defenses during their 1997 to 2011 sample period, but conditioning on removal, the most frequently removed provision was a classified board. We find that among firms with a classified board in our sample, 3.6% remove it during the first decade, 10.5% during the second decade, and 11.9% during the third decade. In addition, among firms without a classified board, 8.3% adopt one during the first decade, 3.0% during the second, and 1.3% during the last decade.

decade slowed 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, Panel B3 shows that declassification rates have increased over a firm's life cycle across IPO cohorts, with the rates generally being faster among all age groups of firms going public during the last two decades.[9]

IV. What Explains the Life-Cycle Trends in Classified Board Usage?

We next examine potential drivers of the classified board trends. We start by investigating how various characteristics associated with the costs and benefits of having a classified board over a firm's life cycle have changed in the last three decades. We next explore alternative explanations to provide a more comprehensive understanding of the observed trends. For our remaining analyses, we focus on tests by decade rather than the IPO cohort because we have a more balanced number of firms across each life-cycle stage over time. Nonetheless, we find that the decade and IPO cohort analyses yield a similar inference.

A. Changes in R&D Expenditures and Intangible Assets

We first consider the evolution of firm characteristics that capture the benefits of classified boards to young firms by examining their investments in innovation-related activities during the last three decades. Investments such as those in R&D and intangible assets create information asymmetries, and the takeover protection provided by classified boards can be value-enhancing to the extent they mitigate the challenge managers face in effectively conveying the long-term benefits of these projects.

Consistent with Field and Lowry (2022), Panel A of Figure 4 shows an increasing trend during the last 30 years in young firms' innovation activities, as measured by R&D expenditures. Based on the model without controls, Panel A1 shows that for the youngest firms aged 0-1, R&D as a percentage of sales averaged 47.6% in the 1990s, 70.9% in the 2000s, and 134.8% in the 2010s. For the most mature firms aged ≥16, these percentages were 2.2%, 10.2%, and 17.8% in the 1990s,

[9] For completeness, Figure IA.2 conducts the same analysis as Figure 3 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 a firm's life cycle and over time.

2000s, and 2010s, respectively. While adding firm-level characteristics and industry fixed effects in Panel A2 and firm fixed effects in Panel A3 changes the average values, the patterns remain largely unaffected. These trends align with our evidence showing that young firms are increasingly likely to use a classified board over the past three decades, suggesting that a classified board can be beneficial by protecting young firms that engage significantly more in R&D initiatives.

[Figure 4 here]

Panel A also shows that not only have R&D expenditures changed over time, but these investments across a firm's life cycle have also evolved over the last three decades. During the last decade, although young firms have significantly more R&D expenditures earlier in their life cycle, they reduce R&D more quickly as they age. As shown in the panel, despite young firms displaying substantial differences in R&D expenditures across the three decades, these differences diminish and converge as firms mature. This adjustment mirrors how firms' use of classified boards changes over time and is consistent with theoretical work that predicts that the costs of employing such a board structure exceed its benefits as the firm matures (Johnson, Karpoff, and Yi (2022)).

For robustness, we also follow Cremers, Litov, and Sepe (2017) and measure investment in innovation using a firm's stock of intangible capital, measured as one minus the ratio of Property, Plant, and Equipment (PP&E) to assets. Panel B of Figure 4 shows trends in intangible assets over a firm's life cycle by decade. While the interpretation is less clear than when we focus on R&D expenditures, the patterns largely hold, suggesting that over the last few decades, younger firms have more intangible assets, and over the most recent decade, maturing firms' balance sheet shifts to having more physical assets more quickly.

B. Changes in Sentiment, Attention, and Scrutiny on Corporate Governance

The corporate accounting scandals of the early 2000s damaged investor confidence and revealed a widespread lack of internal controls and effective governance structures, leading U.S. Congress to pass the Sarbanes-Oxley (SOX) Act in 2002 to protect investors from fraudulent financial reporting. These scandals and the corresponding regulatory response received substantial news coverage, leading to a shift in sentiment against classified boards after 2000. We conjecture that this sentiment shift, combined with increased attention and scrutiny of corporate governance practices, contributed to the more dynamic adjustments of classified boards in recent decades.

Figure 5, Panel A 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 increased in 2002 to over 1,000 articles, clearly reflecting heightened attention to governance. After peaking in 2002, coverage gradually declined, returning to its pre-SOX level by 2010 and remaining at fewer than 200 articles annually. Along with the heightened attention to corporate scandals, the news media also started paying more attention to governance and activism. Panel A also shows that the number of WSJ articles mentioning shareholder activism and corporate governance 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 most of the last two decades.

[Figure 5 here]

Figure 5, Panel B further shows a rise in academic attention to classified boards. The number of Google Scholar articles that mention classified boards increased over tenfold from only 42 in 1996 to 439 in 2018. Requiring each article's title to mention classified boards produces fewer articles, but there is still an upward trend in attention. The trend is similar when we analyze articles posted on the Social Sciences Research Network (SSRN) by counting how many articles mention classified boards in the title, abstract, or keywords. Overall, we document a steady rise in media attention to corporate governance issues and academic attention to classified boards.

C. Changes in Shareholder Collective Action Costs

Prior studies show that collective action and free-riding problems decrease shareholder monitoring and increase managerial entrenchment, reducing firms' ability to optimally adjust takeover defenses (Kahan and Klausner (1996), Hannes (2005, 2006), Johnson, Karpoff, and Yi (2022)). Moreover, shareholders often have diverse investment objectives and time horizons.

Some may be focused on short-term gains, while others prioritize long-term growth. These differing interests can lead to conflicts and difficulties in reaching a consensus on collective actions. In addition, even if shareholders achieve consensus in intended direction of changes, communicating and organizing collective actions among dispersed shareholders can be costly and time-consuming. Shareholders may also have varying levels of access to firm information and heterogeneous views about the costs and benefits of takeover defenses. Thus, information asymmetry or heterogeneity can hinder effective communication and decision-making among shareholders. We hypothesize that collective action costs have decreased over time due to changes in a firm's investor base, improved information environment, and increased shareholder voting participation.

C.1. Rise in Institutional Ownership

Institutional investors are incentivized to call for governance changes to increase firm value (e.g., Lewellen and Lewellen (2022)). These shareholders frequently engage with managers to advocate for governance improvements. Such pressure can help overcome shareholders' collective action problem. The emergence of proxy advisory firms and shareholder services has also contributed to lowering collective action costs. For instance, after the Enron and WorldCom scandals, Patrick McGurn (special counsel to ISS) noted 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, "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 passive index funds that hold a certain amount of a firm's shares per their benchmark weights. In general, investors that do not agree with a firm's governance structures can exert influence by selling shares, 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)).[10]

To get a sense of how passive institutional ownership has changed over time and whether this could have contributed to the life-cycle patterns in firms' use of classified boards, Panel A of Figure 6 plots the average fraction of shares owned by the Big Three index fund managers (i.e., Blackrock, State Street, and Vanguard) by firm age and decade. Panel B is similar, except that it plots the average fraction of a firm owned by 13-F institutional investors designated as quasi-indexers using the classifications from Bushee and Noe (2000) and Bushee (2001).

[Figure 6 here]

Figure 6 shows that, in general, passive institutional ownership increases as firms age and that this increase is faster in more recent decades. Panel A1 shows that Big Three ownership averaged 0.3% for firms aged 0-1 during the 1990s and only 1.0% for the most mature firms aged ≥16. During the 2000s, Big Three ownership increased from 1.5% for the youngest firms to 4.7% for the most mature firms, and during the 2010s, ownership increased from 5.7% to 13.6% from the youngest to most mature firms. Controlling for firm characteristics and industry fixed effects in Panel A2 lessens the steepness in the rise of Big Three ownership as firms mature, but the results continue to show higher Big Three ownership in subsequent decades for each age group. Including firm fixed effects, Panel A3 again reveals a sharp rise in Big Three ownership as firms age, which is steepest in the last two decades. When measuring passive ownership using quasi-indexer classifications, Panel B conveys a similar message as Panel A.

C.2. Changes in Information Heterogeneity

Next, we examine how information heterogeneity among shareholders has changed over time and across a firm's life cycle. As discussed earlier, free-riding and coordination costs can be particularly costly when shareholders have heterogeneous views about the benefits of a takeover

[10] 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 et al. (2022)).

and takeover defenses. Different information or cost bases can result in investors having heterogeneous views (e.g., Bagwell (1991), Dimmock et al. (2018), Levit, Malenko, and Maug (2023)). These arguments imply that collective action costs are lower when shareholders have relatively more homogeneous information and beliefs about firm value. To test this conjecture empirically, we follow Johnson, Karpoff, and Yi (2022) and use a firm's average daily bid-ask spread over its fiscal year, as the bid-ask spread reflects, in part, adverse selection and information heterogeneity among shareholders (e.g., Amihud (2002)). If firms are quicker to remove classified boards due to reduced collective action costs arising from less information heterogeneity, we should find that bid-ask spreads decrease.

Panel A of Figure 7 shows that bid-ask spreads have decreased over time. Without controlling for firm fixed effects, the first decade exhibits the highest information heterogeneity across all stages of a firm's life cycle. It declines slightly over the life cycle when we control for firm fixed effects but remains at a higher level relative to the later decades. In contrast, during the last decade, bid-ask spreads reached their lowest level and maintained this low level across all life-cycle stages.

[Figure 7 here]

C.3. Changes in Hedge Fund Activism

To further illustrate changes in shareholder collective action costs, we examine the evolution of hedge fund activism over time. Hedge fund investors can overcome the collective action problem by taking equity stakes and coordinating efforts, which enables more effective pressuring of firm managers to remove takeover defenses (e.g., Brav et al. (2008), Ge, Tanlu, and Zhang (2016), Boyson, Gantchev, and Shivdasani (2017), Kedia, Starks, and Wang (2021), Johnson, Karpoff, and Yi (2022)). Using data from 1994 to 2018, Panel B of Figure 7 shows that hedge fund activists are more likely to target firms in more recent decades across all age groups, consistent with the view that collective action costs have declined over time and have contributed to changes in the dynamics in classified board usage over a firm's life cycle.[11]

[11] We thank Professor Wei Jiang for generously sharing her extended data from Brav, Jiang, and Kim (2009).

C.4. Shareholder Proposals to Declassify Boards

Given the shift in sentiment and attention, changes in the shareholder base, decreased information heterogeneity, and increased hedge fund activism, we expect shareholders to put more pressure on firms to remove classified boards. Prior studies show that 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), Ge, Tanlu, and Zhang (2016)). Motivated by this work, we analyze proposals to declassify using voting outcome data from Voting Analytics, which is available from 2003 to 2020. Accordingly, we focus on proposals 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 concerns 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. Voting Analytics would capture these proposals in cases (ii) and (iii). 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 considered 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.

Panel C of Figure 7 shows that the fraction of firms with a classified board in year *t* or *t*-1 that vote on proposals to declassify their boards increases over a firm's life cycle and increases faster over the most recent decade. Without controls, Panel C1 shows that the youngest firms aged 0-1 had a similar likelihood of receiving proposals in the 2000s and 2010s, at 0.4% and 0.2%, respectively. However, this rate sharply diverges for older age groups. For firms aged 2-3 in the 2000s, 0.6% were targeted with a proposal, but 2.8% of firms were targeted in the 2010s. The gap in the 2010s continues to be higher than that in the 2000s until firms reach age ≥16, with 5.5% and

5.4% of firms receiving proposals in the 2000s and 2010s, respectively. The pattern is similar in Panel C2 when we control for firm characteristics and industry fixed effects. When we control for firm fixed effects in Panel C3, after age 0-1, firms in the 2010s are more likely to receive a proposal than those in the 2000s at every point in their life cycle. Overall, these results suggest that shareholders have become more active in proposing changes and applying pressure on firms to declassify (e.g., Belinfanti (2008), Dyck, Volchkova, and Zingales (2008), Appel, Gormley, and Keim (2016), McCahery, Sautner, and Starks (2016), Abramova, Core, and Sutherland (2020)).

D. Further Analysis of Changes in Sentiment and Attention

D.1. Institutional Ownership and Changes in Sentiment

Given our finding that passive institutional ownership has steadily increased over time, we investigate whether changes in their attitudes toward classified boards play a role in explaining the trends. To do so, we first regress our classified board indicator on Big Three and non-Big Three ownership interacted with five-year interval dummy variables across four age groups: 0-2, 3-6, 7-10, and ≥11. In these analyses, we 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.

[Table III here]

Columns (1) to (4) of Table III tabulate the coefficients on these interaction terms. Overall, the relation between having a classified board and institutional ownership is relatively flat for the youngest firms from 1991 to 2020. However, for the most mature firms aged ≥11, the coefficients on institutional ownership were positive and significant during the 1990s and early 2000s.[12] This positive correlation may be attributed to several factors. First, institutional investors may have

[12] We note that the age ≥11 group has a substantially larger number of observations than the other age groups. To examine whether the life-cycle effect stabilizes once firms reach 11 years or older, we separate this group into two distinct categories: firms aged 11–15 and those older than 16. Rerunning the tests in Tables III to V, we find that the results generally align with the same overall life-cycle patterns, with both groups exhibiting similar behavior, though the effects are stronger for firms aged 16 years or older.

supported the adoption of classified boards to enhance the board's negotiating power during the active hostile takeover market of the 1980s. Moreover, institutional investors with a long-term focus likely valued governance stability and continuity, perceiving classified boards as beneficial during the 1990s. However, following corporate scandals and changes in market sentiment, institutional investors became key proponents of removing classified boards, as evidenced by the negative relation after 2005. In columns (5) to (8), we find similar results when we regress our classified board indicator on quasi-indexer and non-quasi-indexer ownership interacted with the five-year interval dummy variables. In sum, our results imply that passive institutional ownership has risen over time, particularly in the latter half of the sample, and that this rise in ownership associates positively with increased governance scrutiny and board declassification.[13]

D.2. Changes in Attention and Classified Boards

We further assess the role of increased attention and scrutiny of governance practices on classified board trends by examining how being listed on the S&P 1500 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)). In addition, because the media, analysts, and academics cover S&P 1500 and larger firms more intensely, the governance practices of these firms are especially likely to be scrutinized and influenced by this heightened coverage.

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 the market value of equity across the four

[13] Related, we investigate whether this increase in passive institutional ownership pressures firms to behave sub-optimally and declassify their boards sooner than they should. First, based on analysis below of announcement cumulative abnormal returns (CARs) around declassification (see Section V.B), we split firms based on high and low institutional ownership and test CARs separately for each subsample (see Figure IA.3). There is some suggestive evidence that firms with more passive institutional ownership have higher CARs, which is inconsistent with institutional pressure forcing firms to declassify their boards suboptimally. We also compare classified board usage across the life cycle between firms with high and low institutional holdings and find that the more dynamic adjustment in the use of classified boards in recent decades is concentrated among firms with high institutional ownership (see Figure IA.4). This supports the view that institutional investors recognize how the costs and benefits of classified boards evolve over a firm's life cycle and push for optimal, rather than suboptimal, adjustments of this takeover defense.

age groups, tabulating results that include firm-level controls and firm fixed effects. Columns (1) to (4) of Table IV show that until 2010, the most mature firms in the S&P 1500 were significantly more likely to have classified boards than firms not in the S&P 1500. After 2010, this relation became significantly negative. For younger firms, there is little difference in classified board usage between index and non-index firms over time.

[Table IV here]

When we proxy for governance scrutiny using firm size, columns (5) to (8) show that, except for the youngest firms, larger firms were significantly more likely to have a classified board until around 2005. After this year, the relation is mostly insignificant for firms aged 3-6 but significantly negative for the more mature firms aged 7 and older. For the youngest firms aged 0-2 years, the relation between firm size and having a classified board has been largely flat over time.[14]

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.[15] We require both groups to have a classified board in the years before treatment and keep years ±3 around the treatment year.[16] We then regress our classified

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[14] For completeness, we examine the impact of investments in innovative activities and bid-ask spreads on classified board usage over time in Table IA.II. When we focus on the most mature firms, the results are broadly consistent with the view that firms and investors have had an increasingly better understanding of the cost-benefit trade-offs of classified boards over time, which contributed to the more optimal adjustments that we observe in more recent decades. For firms aged 11 years or older, the relation between R&D and having a classified board shifted to significantly positive in the 2010s. Similarly, the coefficients on bid-ask spreads became positive and significant after 2005. We find a similarly signed but statistically insignificant pattern for mature firms with investments in intangible assets.

[15] We estimate the likelihood that a firm is in the S&P 1500 using a logit model and the covariates *Ln(MVE), IO,* and *Delaware*. We then match S&P 1500 firms to non-S&P 1500 firms so 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.

[16] 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 624 treatment firms and 1,159 control firms.

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 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 indicate 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, it and its corresponding matched firms would be included in the 2011 to 2020 cohort and have sample years of 2009 to 2015 included in the regression.

[Figure 8 here]

Figure 8, Panel A (Panel B) plots the coefficients from these regressions without (with) firm-level controls. Both figures show statistically significant negative coefficients in the 2011 to 2020 decade. For this decade, firms are significantly less likely to keep a classified board in the three years after joining the index. In contrast, firms joining the S&P 1500 index in the 1991 to 2000 and 2001 to 2010 decades are equally likely to maintain their classified boards as the control firms.

In Panels C and D, 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, even in the last decade from 2011 to 2020. In contrast, mature firms' likelihood of having a classified board decreased significantly after being added to the index during the 2011 to 2020 decade, whereas there was no change in likelihood during the earlier decades.

In summary, the findings in this section largely support the view that the increased benefits of classified boards for young firms, changing attitudes and scrutiny of governance, and reduced collective action costs have led firms to adjust their classified boards more dynamically over time. Nevertheless, we do not intend to claim causality, and we acknowledge the difficulty in accurately identifying all possible factors that could contribute to these patterns, especially given that time trends are frequently influenced by multiple factors simultaneously.

E. Other Factors and Alternative Explanations

In this section, we explore alternative explanations for the trends we document in classified board usage. First, takeover defenses can benefit firms by protecting important stakeholder relationships from being disrupted by a takeover. Figures IA.5 and IA.6 show that changes in the importance of stakeholders and other proxies for the costs and benefits of maintaining a classified board over a firm's life cycle over time do not coincide with the trends we observe in the use of classified boards. These proxies follow from Cremers, Litov, and Sepe (2017) and Johnson, Karpoff, and Yi (2015, 2022) and include proxies related to the importance of customers, suppliers, strategic alliances, and joint ventures. We also show no related trends in the marginal value of cash, sales to large customers, diversifying acquisitions, and durable product sales.

Second, if mature firms were less likely to be acquisition targets during the last two decades compared to the 1990s, then their need for a classified board as a takeover defense would have decreased during this period. Hence, firms in the more recent years of our sample might declassify their boards sooner in their life cycle because they do not need board classification for takeover protection. Figure IA.7 shows that changes in the market for corporate control cannot explain the different life-cycle effects on classified board usage across recent decades, as these changes appear across all firm-age groups.

Third, combined with our findings in Figure 2 that the trends in classified board usage persist in models with firm-level controls and firm fixed effects, Figure IA.8 shows that the patterns continue to hold after controlling for other time-varying firm characteristics, including firm size squared and cubed, Tobin's Q, profitability, book leverage, capital expenditures, stock return volatility, share turnover, and analyst coverage. Thus, underlying changes in these firm characteristics over time do not explain our findings.

Fourth, survivorship bias characterized by firms with classified boards experiencing a higher attrition rate as they age, especially in recent decades, cannot explain our findings. Similar to the approach in Lemmon, Roberts, and Zender (2008) and Johnson, Karpoff, and Yi (2022), Figure IA.9 shows that restricting the sample to firms that survive for the entire decade has little effect on the trends in classified board usage.

Finally, we show that while firm age and market capitalization are correlated ($\rho = 0.27$), firm age is a distinct proxy of a firm's life cycle. In particular, it captures the net effect of the costs and benefits associated with classified boards rather than simply reflecting firm size. In Table IA.III, we assess the overlap between firm age and market capitalization by tabulating a 5×5 matrix of age and size where we independently sort both variables into quintiles. If firm age primarily captures firm size, observations should lie disproportionately on the diagonal. However, apart from quintile 5 for both size and age, the other diagonal groupings do not exhibit a disproportionately higher number of firms. Further, we repeat the analysis in Figure 2, replacing firm age groups with size. Figure IA.10 shows an inverse u-shape between classified board usage and firm size when not controlling for firm fixed effects. This pattern holds in each decade. After including firm fixed effects, we find a slightly increasing relationship between size and classified board usage for the first two decades, and a noticeable decline in the use of classified boards among the largest firms during the last decade. Overall, using firm size rather than firm age yields dissimilar trends in classified board usage.

V. Life-Cycle Trends in the Relation Between Classified Boards and Firm Value

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

A. Classified Boards and Tobin's Q

Following Johnson, Karpoff, and Yi (2022), Table V 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 Johnson, Karpoff, and Yi (2022), we find a significantly positive relation between firm value and having a classified board for newly public firms (*t*-statistic = 2.76). However, this relation becomes significantly negative for firms aged two years and older (*t*- statistics ranging from -3.87 to -2.23).

[Table V here]

These findings support the claim that classified boards are valuable for newly public firms, but their costs increasingly exceed their benefits as firms mature. This pattern can 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)). In contrast, if classified boards were removed once their costs outweighed their benefits, there would be no value reversal effect over a firm's life cycle in equilibrium.

Our paper's key findings suggest that reduced collective action costs and increased institutional ownership and scrutiny of governance practices have pressured firms to adopt more optimal governance policies in recent decades by declassifying their boards at a younger age before the defense becomes value-destroying. We test this implication in Panels B to D by conducting the same 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 in Panel A. The value reversal effect across age groups becomes less pronounced in the 2000s, as shown in Panel C. Finally, Panel D shows that, except for firms aged 3-4 (*t*-statistic = -2.02), there is no longer a statistically significant relation between classified boards and firm value across age groups in the most recent decade.[17,18] These results suggest that classified boards have been used more optimally during the 2010s, eliminating the value reversal effect from the prior decades.

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[17] We conducted tests that compared coefficients of same-aged firms between the first and last decades and found statistically significant differences among the coefficients of the most mature firms (i.e., those aged 10 years or older). For the other age groups, the coefficients were not statistically different.

[18] In Table IA.IV, we account for the findings in Frakes (2007) that Delaware incorporation could affect firm value differentially over time due to changes to Delaware law in the mid-1990s. We do so by adding a Delaware dummy and its interaction with year fixed effects as additional control variables in all panels. Our findings are similar with the inclusion of these additional controls.

The results in Panels B and C also show that the positive relation between classified boards and the valuations of newly public firms (age 0) became insignificant in the following year (age 1). The initial positive relation indicates that the benefits of classified boards outweighed their costs during this period for newly public firms and suggests that more firms should have had a classified board at IPO. Supporting this view, Figure IA.2 shows that during this period, classified boards were more likely to be adopted by firms in the years immediately following their IPO.[19] Table V, Panel B also shows that the relationship between classified boards and valuations turns marginally negative by age 2, and significantly so by age 3-4. While we do not have a complete explanation for this sudden shift, one possible interpretation is that investors and market participants anticipated that firms would start removing classified boards in the few years post-IPO before the costs of the defense exceeded its benefits and because declassification typically takes time to implement to fully phase out staggered director elections. However, when firms failed to follow through on these expectations, which was common in the 1990s due to high collective action costs, the market reacted negatively.

B. Announcement Returns Around Board Declassification

Next, we examine how the market responded to firms declassifying their boards over time. In Figure 9, we perform a short-run stock return event study around the date of the shareholder meeting when firms vote to approve a 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 CARs over the ±2-days around the announcement of the successful declassification vote. We estimate the 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

[19] Indeed, when we analyze the likelihood of classified board adoptions in the years right after an IPO, we find that during the 1990s (2000s), 2.2% (1.4%), 2.1% (0.7%), and 1.9% (0.1%) of firms adopted classified boards in the one, two, and three years following their IPO, respectively. Conversely, in the 2010s, these percentages are 0.9%, 0.1%, and 0.0% within the same period. Therefore, the cumulative probability of adopting a classified board within three years following the IPO is 6.2%, 2.2%, and 1.0% for the three decades, respectively, consistent with firms underusing classified boards at the time of their IPO during the earlier decades.

regress CARs on year dummies and estimate models without any controls and with firm-level controls and industry fixed effects.

[Figure 9 here]

Focusing on the models that control for firm-level characteristics and industry fixed effects, the figure shows that, on average, CARs are positive but statistically insignificant across the full sample period (*p*-value = 0.588). However, the results suggest that declassification proposals were particularly well received in 1999 to 2000, as evidenced by the significant CARs ranging from 5.9% to 6.1%. 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 firm value.[20] The insignificant stock price reactions to boards declassifying after 2000 may reflect partial anticipation by the stock market, as proposals to remove classified boards were almost always approved in the more recent decades, minimizing uncertainty about the likelihood of board declassification by the firm.[21,22]

C. Changes in Accounting Performance after Board Declassification

We supplement our short-run event study analyses by examining how accounting performance changed in the years after board declassification. The hypothesis is that if declassification of

[20] We also conducted statistical tests to compare CARs across different decades to assess whether the observed differences are significant. We find that only the CARs from 2001 to 2010 are statistically smaller than those from the 1990s. In addition, in Figure IA.11 we analyze by decade and firm age the CARs surrounding a firm's announcement to declassify. However, an important caveat when interpreting the findings of these tests that divide firms by decade and age is that they result in very few observations for certain decade and firm age groups, increasing the noisiness of the estimates. Nevertheless, we find suggestive evidence of higher CARs during the first decade when focusing on the mature firms. For the last two decades, CARs have been similar across the age groups.

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

[22] We note that in 2009, the market's reaction to declassification was significantly negative, even after we control for industry and firm characteristics. A potential explanation could be that takeover defenses can preserve firm value during turbulent market times (e.g., Eldar and Wittry (2021), Guernsey, Sepe, and Serfling (2022)).

mature firms decreases agency costs and increases operational efficiency, accounting performance should improve as well. Similar to our analysis of firms being added to the S&P 1500, we create a stacked difference-in-differences research design, where we use a propensity-score-matched sample that pairs treatment firms (firms that declassify their board in year *t*) to control firms (firms that have a classified board in year *t*-1). Figure 10 shows that firms declassifying their boards in the first decade experienced an increase in operating return on assets (ROA) in the years following declassification, whereas there was no such change in performance during the latter decades. Moreover, the improvement in ROA after declassification during the first decade was concentrated in mature firms. These findings suggest that classified boards were maintained for too long over firms' life cycles during the first decade, with performance negatively affected as a result.

[Figure 10 here]

VI. Conclusion

This paper investigates the evolution of classified board usage throughout a firm's life cycle. We build a novel data set that tracks the use of classified boards by nearly all U.S. publicly traded firms from 1991 to 2020. Based on this data set, we investigate how firms from specific cohorts, categorized by decade or IPO year, changed their use of classified boards as they aged. We find that during the 1990s, classified boards exhibited a high degree of persistence, with infrequent removal. However, during the 2000s, firms were more likely to declassify their boards as they matured. This trend was most pronounced in the most recent decade, with firms adjusting their classified boards more quickly throughout their life cycle.

Additional analyses suggest that the costs and benefits associated with classified boards have changed over time. One main benefit of having a classified board is that it protects firms that concentrate on long-term investments, particularly those with high information asymmetry, such as investments in R&D and intangibles. Over the last 30 years, we find that there has been a growing trend among young firms towards increased investment in R&D and intangible assets, making them more likely to benefit from having a classified board. Further, we observe a significant decline in collective action costs over time, attributable to heightened governance scrutiny, increased passive institutional ownership and hedge fund activism, and reduced information heterogeneity among investors. These results suggest that the evolving costs and benefits associated with classified boards and reduced collective action costs have contributed to the more dynamic adjustments in classified board usage in recent decades.

Further supporting the view that high collective action costs and free-riding problems prevented firms from optimally adjusting their classified boards to maximize firm value in the earlier decades, the relation between classified boards and valuations was positive (negative) for young (mature) firms during the 1990s and early 2000s. This evidence suggests that firms maintained classified boards 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 findings on the effects of decade and IPO cohorts on classified board usage have several implications for researchers. In particular, our results suggest that future work examining takeover defense usage over a firm's life cycle and its relation with shareholder value should account for the underlying governance landscape during the study period. The results also point to problems with not only a "one-size-fits-all" approach to takeover defenses but also with "one size fits all *always.*" From a methodological perspective, we show how advances in machine learning can be used to create new comprehensive data sets, which offers many opportunities for future research. For instance, future work could use our methodology to construct data sets for additional takeover defenses (e.g., the other components in the E-index) and investigate the role of these defenses in deterring takeovers across a firm's life cycle and whether these effects have changed over time.

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Appendix. Variable Definitions

This table provides 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)
Age	The number of years that a firm has been publicly traded, based on when a firm first has nonmissing share price information in the Compustat database.
Assets	Book value of assets (*at*) (in millions of 2017 dollars).
Big 3 IO	Percentage of a firm's shares owned by the Big Three (i.e., Blackrock, State Street, and Vanguard) institutional investors at the end of a firm's fiscal year.
CAR [-2, +2]	Cumulative abnormal return over the five-day window surrounding the annual shareholder meeting date, where the meeting date is day 0. Parameters used to calculate CARs are estimated using the market model and the 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 does not have 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.
MVE	Market value of equity (*prcc_f***csho*) (in millions of 2017 dollars).
IO	Percentage of a firm's shares owned by institutional investors at the end of a firm's fiscal year.
Quasi IO	Percentage of a firm's shares 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*).

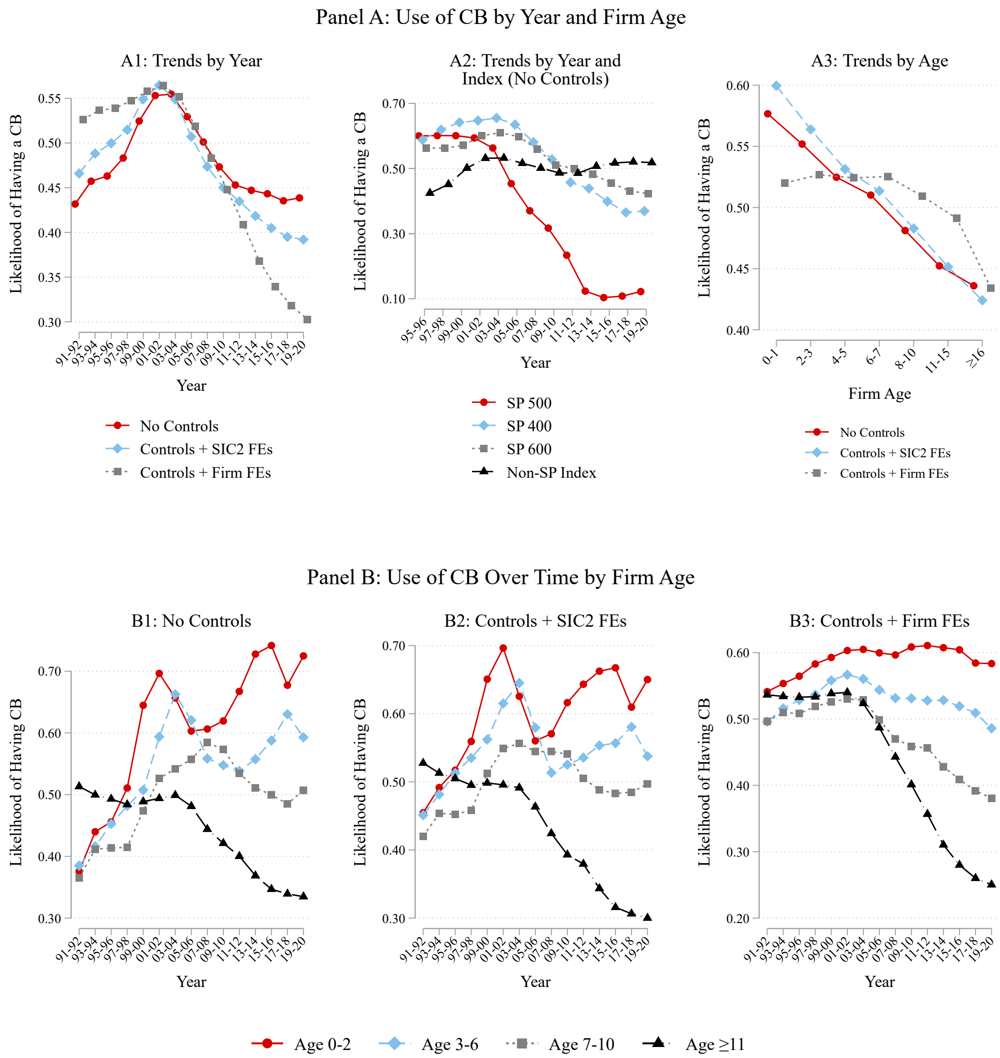
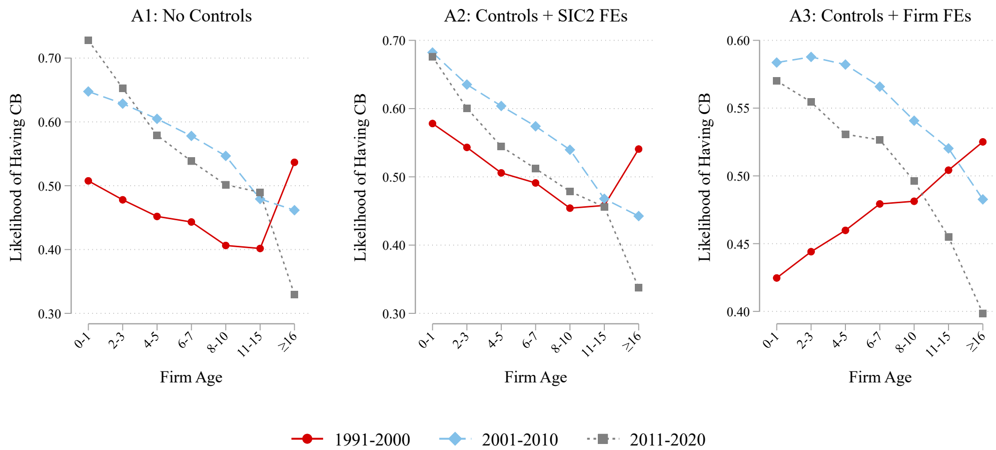


Figure 1. Classified board usage by year and firm age. The figure shows the fraction of firms with a classified board by year and firm age. The panels plot the coefficient estimates (β_{1991}-β_{2020} and ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of the classified board indicator (*CB*) on controls:

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

where $Year_t$ 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 the Appendix), which include $Ln(MVE_{t-1})$, IO_t, $Delaware_t$, and $S\&P\ 1500_t$, and 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

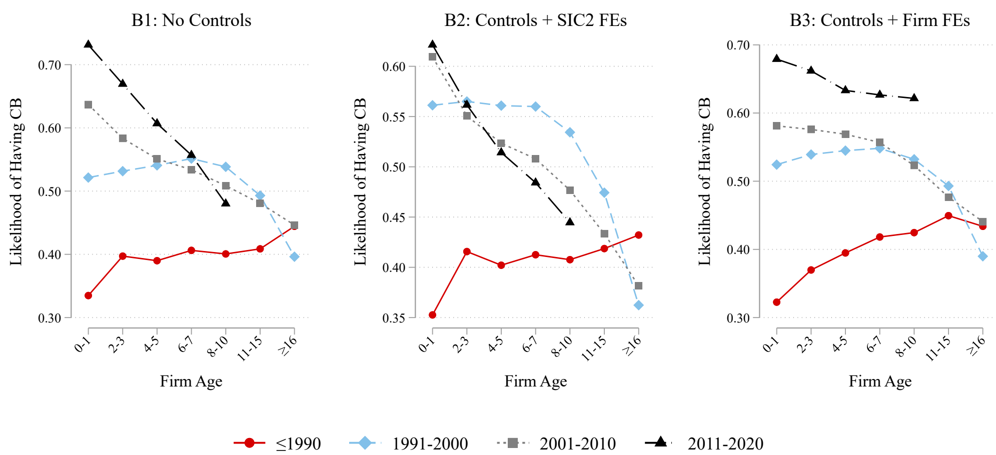
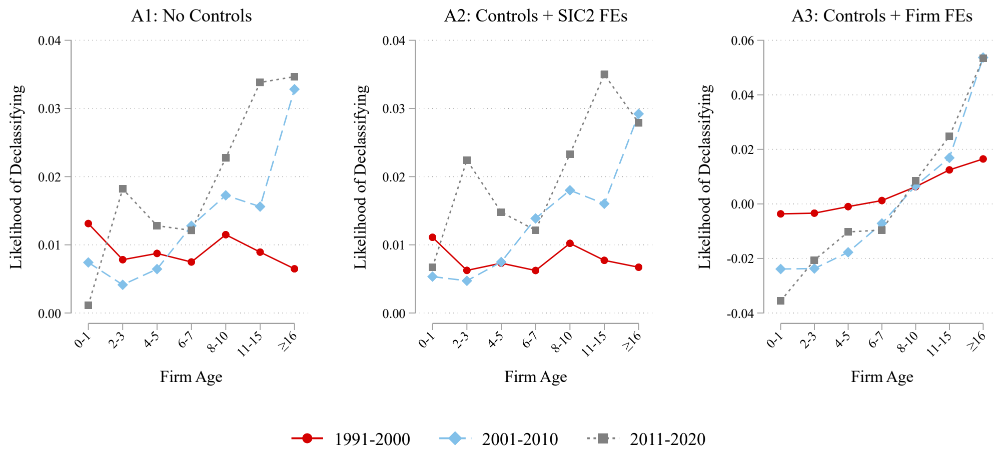


Figure 2. Classified board usage by firm age, decade, and IPO cohort. Panel A (B) shows the fraction of firms with a classified board by firm age group and decade (IPO cohort). The panels plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of the classified board indicator (*CB*) on controls (regressions are estimated separately for each decade in Panel A and for each IPO cohort in B):

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

where Age_{it} equals one if firm age is in age group *a,* and zero otherwise, X_{it} are firm-level characteristics (defined in the Appendix), which include $Ln(MVE_{t-1})$, IO_t, $Delaware_t$, and $S\&P\ 1500_t$, and 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

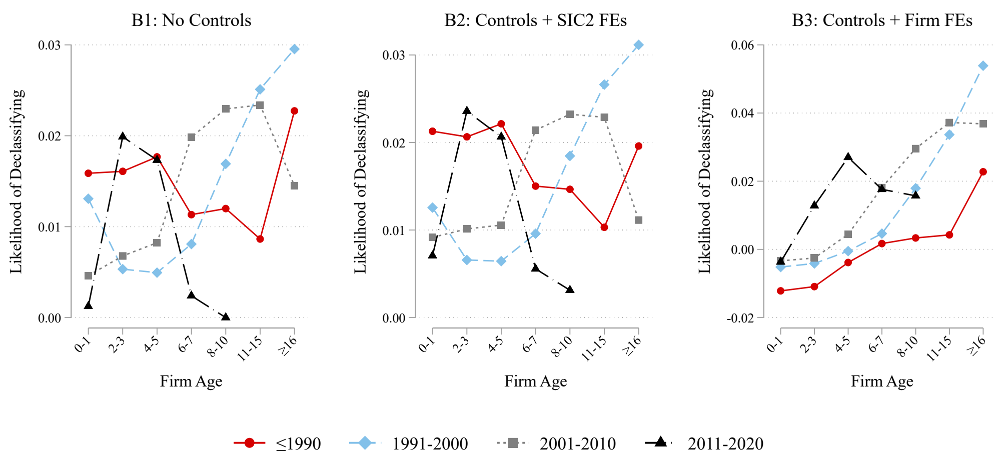
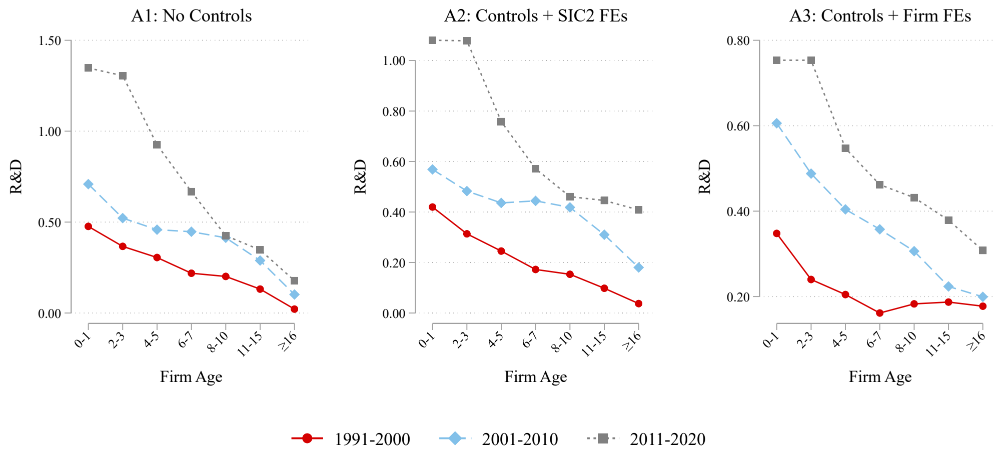


Figure 3. Board declassification by firm age, decade, and IPO cohort. Panel A (B) shows the likelihood of a firm declassifying its board over time by firm age group and decade (IPO cohort). The panels plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of the board declassification indicator variable (*Declass*) on controls (regressions are estimated separately for each decade in Panel A and for each IPO cohort in Panel B):

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

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

Panel A: Research and Development Expenditures



Panel B: Intangible Assets

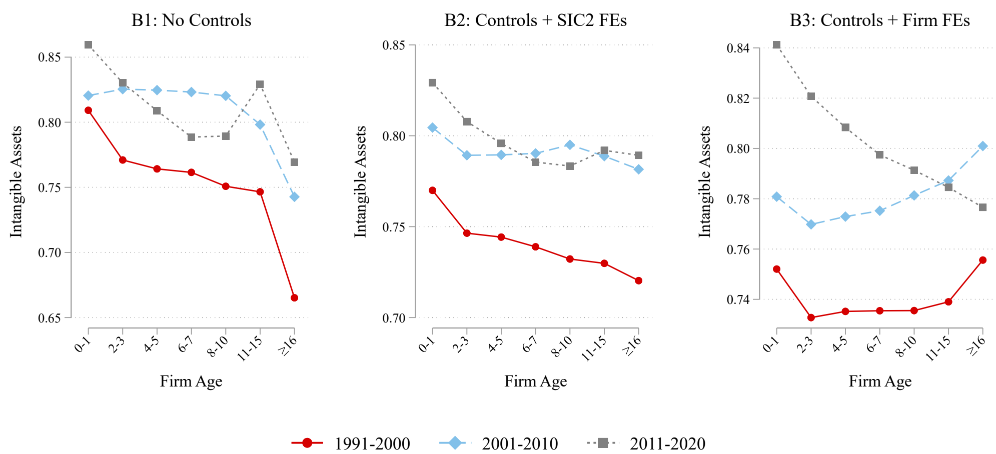


Figure 4. R&D expenditures and intangible assets by firm age and decade. Panel A (B) shows R&D expenditures (intangible assets) by firm age group and decade. The panels plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of R&D expenditures scaled by sales (*xrd/sale*) and intangible assets (1-*ppent/at*) on controls (regressions are estimated separately for each decade):

$$R\&D_{it} \text{ or } Intangibles_{it} = \sum_{a=0}^{\geq 16} \omega_a Age_{it} + \Gamma X_{it} + \eta_k + \gamma_i + \varepsilon_{it},$$

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

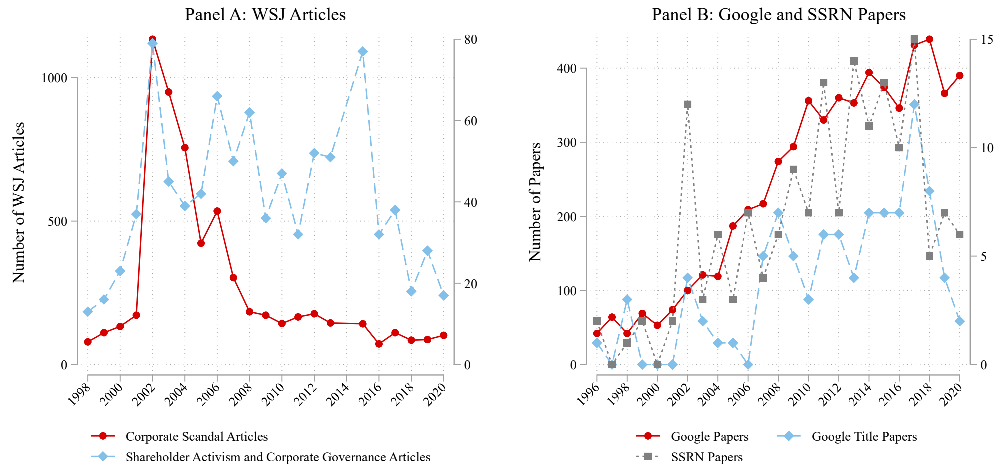


Figure 5. WSJ and academic articles. Panel A plots the number of articles published in the *Wall Street Journal* (WSJ) that cover corporate scandals and shareholder activism and corporate governance from 1998 to 2020. 1998 is the earliest year for which we have WSJ article text. To identify relevant 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." The number of "Shareholder Activism and Corporate Governance Articles" are shown on the right-hand-side axis. Panel B plots the number of academic articles on classified boards from 1996 to 2020, which comprise those with either of the keywords "classified board(s)," or "staggered board(s)." The number of "Google Title Papers" and "SSRN Papers" are shown on the right-hand-side axis.

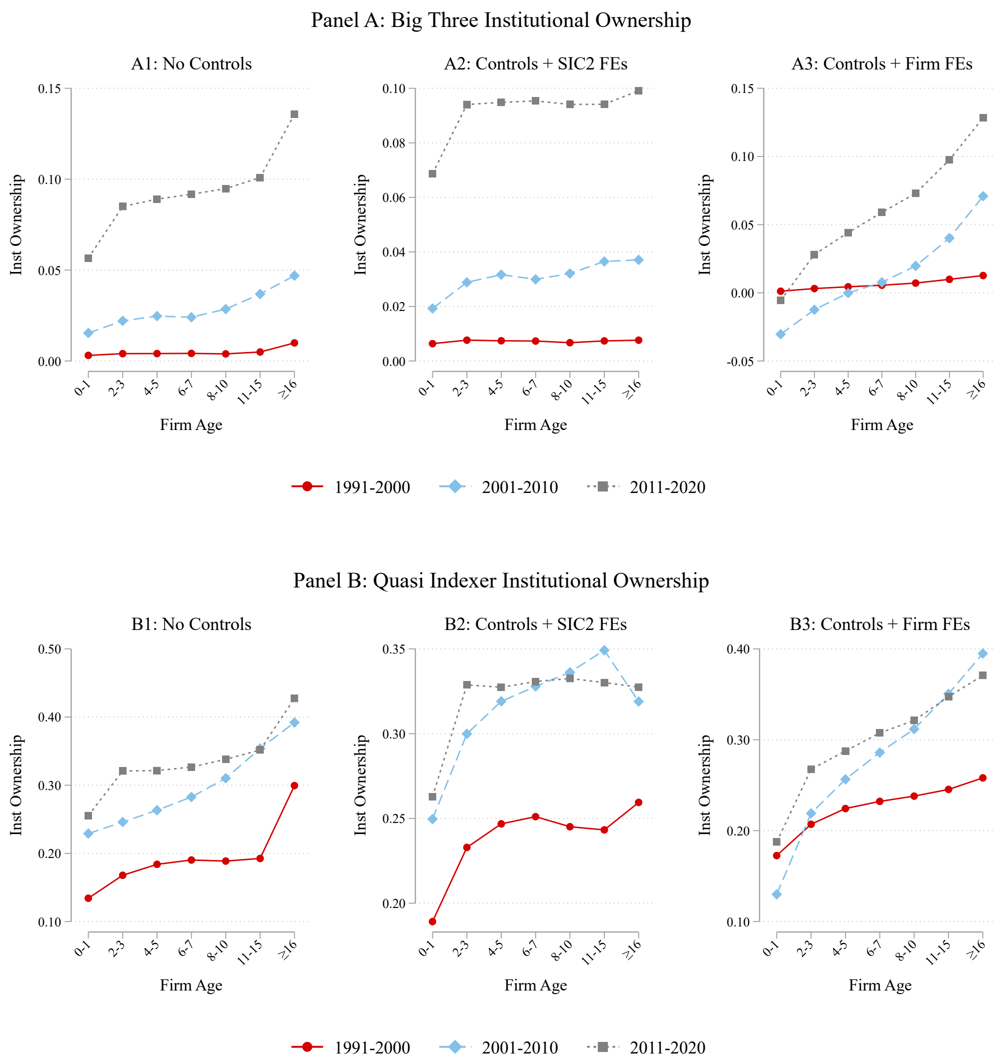


Figure 6. Passive institutional ownership by firm age and decade. This figure shows passive institutional ownership by firm age group and decade. The panels plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of *Big 3 IO* (Panel A) and *Quasi IO* (Panel B) on controls (regressions are estimated separately for each decade):

$$Big\ 3\ IO_{it}\ or\ Quasi\ IO_{it} = \sum_{a=0}^{\geq 16} \omega_a Age_{it} + \Gamma X_{it} + \eta_k + \gamma_i + \varepsilon_{it},$$

where *Big 3 IO* is the fraction of a firm's shares owned by the Big Three institutional investors (Blackrock, State Street, and Vanguard), *Quasi IO* is the fraction of a firm's shares owned by institutional investors classified as quasi-indexers in Bushee and Noe (2000) and Bushee (2001), Age_{it} equals one if firm age is in age group *a,* and zero otherwise, X_{it} are firm-level characteristics (defined in the Appendix), which include $Ln(MVE_{t\text{-}1})$, $Delaware_t$, and $S\&P\ 1500_t$, and η_k and γ_i are two-digit SIC industry and firm fixed effects, respectively.

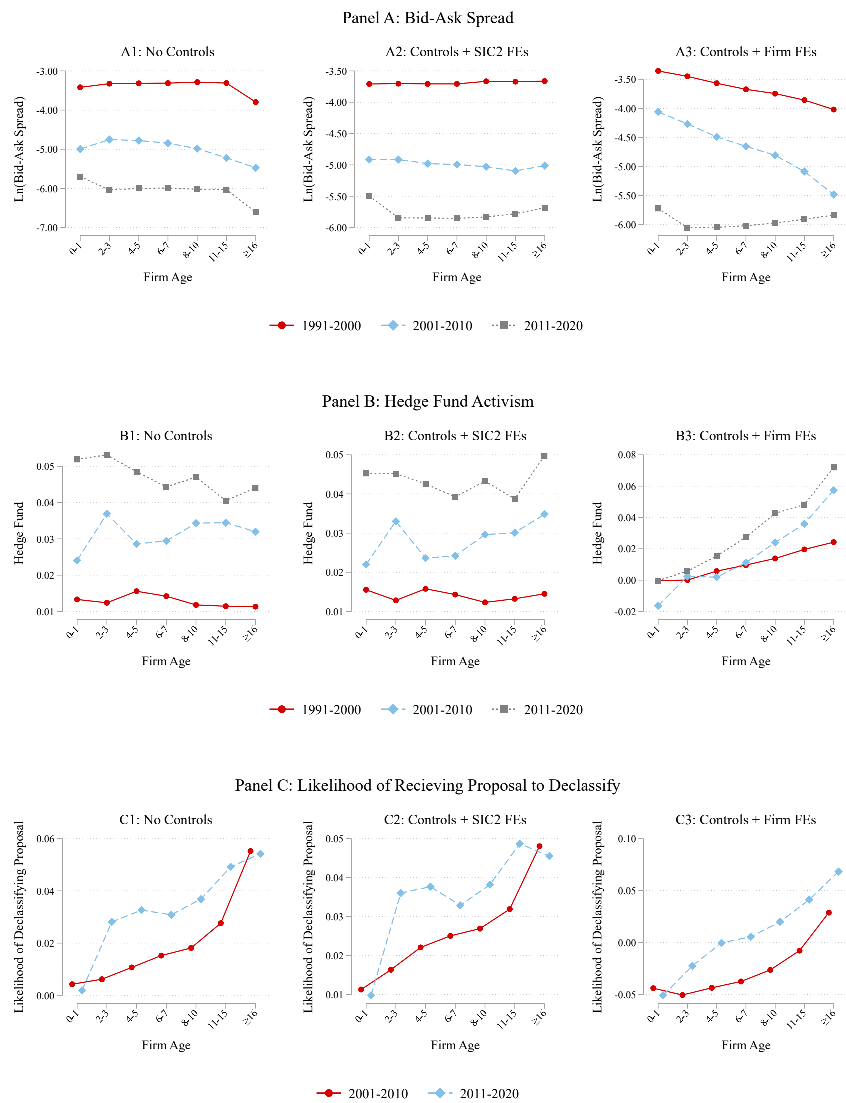


Figure 7. Cost of collective action by firm age and decade. This figure shows the bid-ask spreads [*Ln*(*Bid-Ask Spread*)] in Panel A, the likelihood of being targeted by hedge fund activism (*Hedge Fund Activism*) in Panel B, and the likelihood of firms receiving proposals to declassify their board (*Proposal*) in Panel C by firm age group and decade. The sample period is from 1991 to 2020 in Panel A, 1994 to 2018 in Panel B, and 2003 to 2020 in Panel C. The panels plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of *Ln*(*Bid-Ask Spread*), *Hedge Fund Activism*, and *Proposal* on controls (regressions are estimated separately for each decade):

$$Ln(Bid\text{-}Ask\ Spread)_{it}\ or\ Hedge\ Fund\ Actvism_{it}\ or\ Proposal_{it} = \sum_{a=0}^{\geq 16} \omega_a Age_{it} + \Gamma X_{it} + \eta_k + \gamma_i + \varepsilon_{it},$$

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

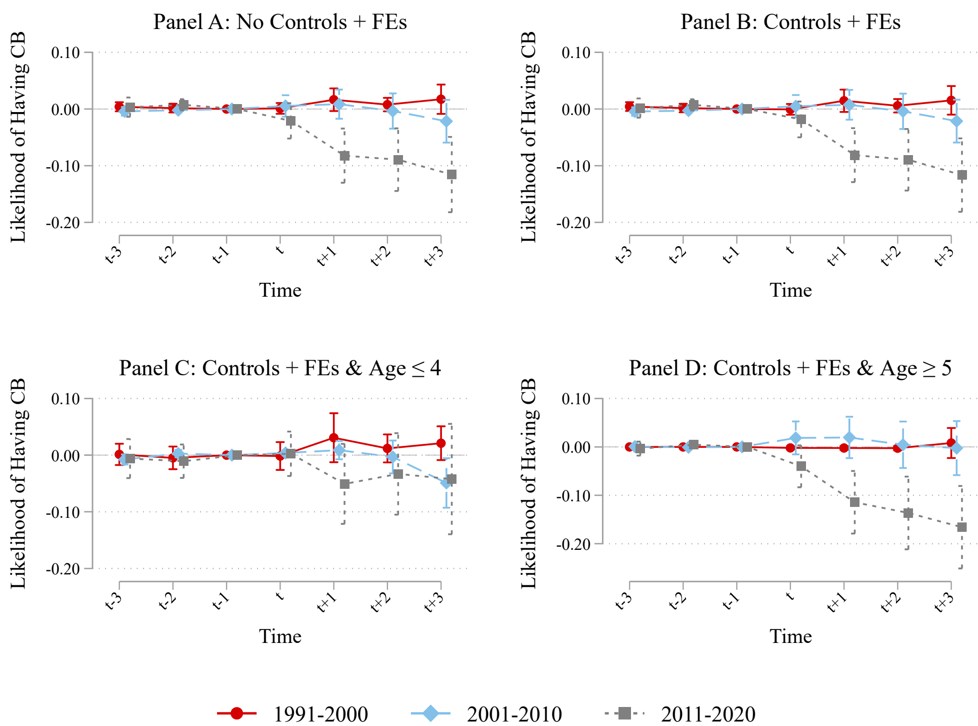


Figure 8. Effect of being added to the S&P 1500 on classified board usage by time and firm age. Panels A to D plot the coefficient estimates (β_{-3}- β_3) from OLS regressions using a propensity-score-matched sample examining the effect of joining the S&P 1500 on the likelihood of having a classified board during the following treatment cohorts: 1991 to 2000, 2001 to 2010, and 2011to 2020. The regression is

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

where 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, δ_{jt} are treatment cohort-year fixed effects, X_{ij} are firm-level characteristics fixed at time *t*-1 for each treatment cohort *j* (defined in the Appendix), which include *Ln*(*MVE*), *IO,* and *Delaware* ,and $Post_{jt}$ equals one for 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.

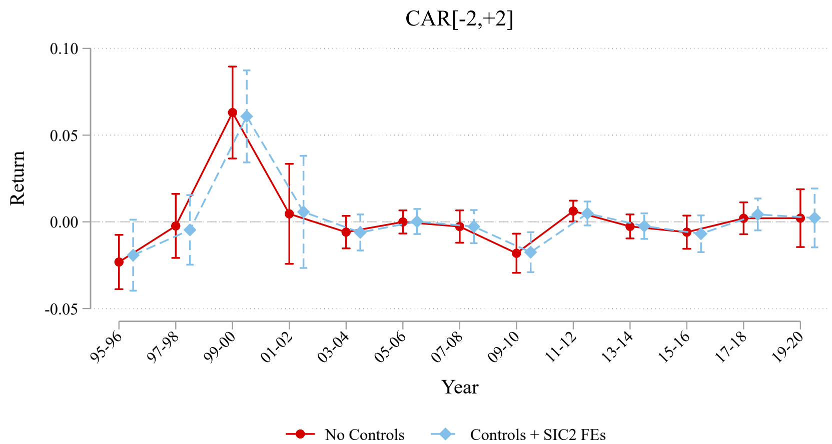


Figure 9. Announcement CARs to board declassification over time. The figure tabulates ±2-day CARs around annual shareholder meetings that vote to declassify a firm's board over the period 1995 to 2020. Parameters used to calculate CARs are estimated using the market model and CRSP equal-weighted index 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 OLS regression

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

where $Year_t$ equals one for observations in year group t, and zero otherwise, X_{it} are firm-level characteristics measured before the announcement date (defined in the Appendix), which include $Ln(MVE_{t-1})$, IO_{t-1}, $Delaware_{t-1}$, and $S\&P\ 1500_{t-1}$, and η_k are two-digit SIC industry fixed effects. 90% confidence intervals based on standard errors clustered by firm are reported.

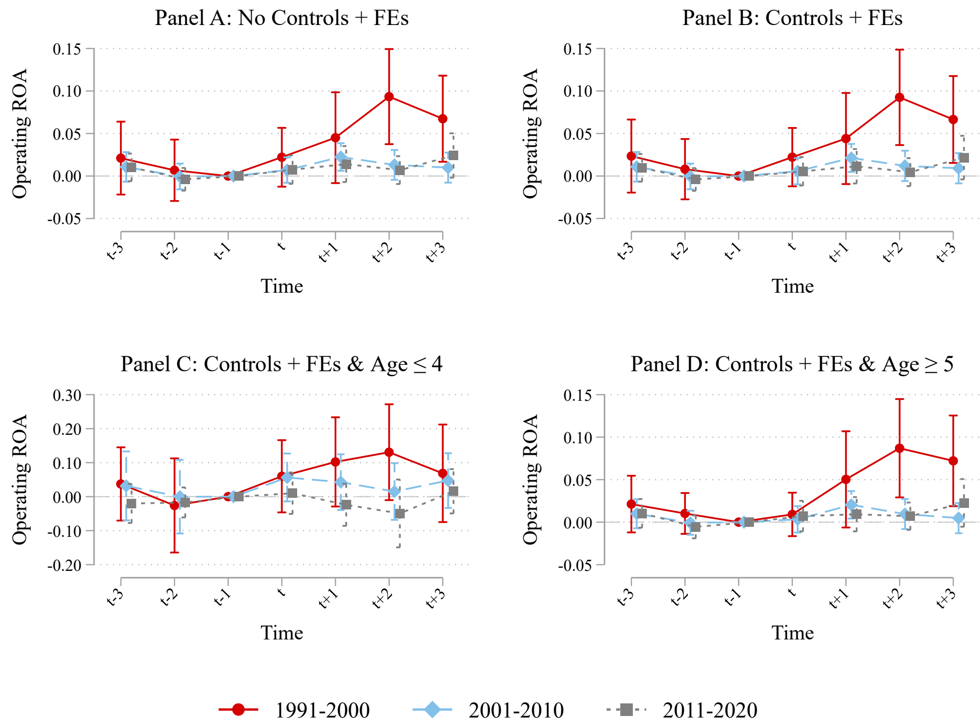


Figure 10. Effect of removing a classified board on firm performance. Panels A to D plot the coefficient estimates (β_{-3}- β_3) from OLS regressions using a propensity-score-matched sample examining the effect of declassifying a board on a firm's ROA during the following treatment cohorts: 1991 to 2000, 2001 to 2010, and 2011 to 2020. The regression is

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

where the dependent variable $OROA_{ijt}$ equals operating return on assets for firm i for treatment cohort j in year t, $Treat_{ij}$ equals one for the treatment firms that remove their classified board, 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, δ_{jt} are treatment cohort-year fixed effects, X_{ij} are firm-level characteristics fixed at time t-1 for each treatment cohort j (defined in the Appendix), which include *Ln*(*MVE*), *IO,* and *Delaware*, and $Post_{jt}$ equals one for 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.

Table I
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 in means and medians between firms with classified boards and unitary boards, respectively, at the 10%, 5%, and 1% levels are denoted with *, **, and *** in the Classified Board Sample's mean and P50 columns. Standard errors are clustered by firm. Variables are defined in the Appendix.

	Classified Board Sample (Obs = 66,262)			Unitary Board Sample (Obs = 70,770)		
	Mean	P50	Std Dev	Mean	P50	Std Dev
MVE	2062.0***	361.5***	6057.1	3509.6	255.8	10295.5
Ln(MVE)	5.925***	5.890***	1.879	5.748	5.544	2.267
IO	0.453***	0.436***	0.305	0.413	0.361	0.286
Delaware	0.572***	1.000	0.495	0.540	1.000	0.498
S&P 1500	0.288	0.000	0.453	0.285	0.000	0.451
Age	13.61***	9.00***	12.38	16.05	12.00	13.50
Ln(Age)	2.255***	2.303***	1.012	2.456	2.565	0.968

Table II
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) to (4) ((5) to (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 (regressions are estimated separately for each decade in columns (2) to (4) (IPO cohort in columns (5) to (8)):

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

where Age_{it} equals one if firm age is in age group *a,* and zero otherwise, X_{it} are firm-level characteristics (defined in the Appendix), which include $Ln(MVE_{t\text{-}1})$, IO_t, $Delaware_t$, and $S\&P\ 1500_t$, and γ_i are firm fixed effects. In these tests, the youngest firms aged 0-1 are the excluded reference group and are analogous to Figure 2, Panels A3 and B3. *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	0.007***	0.019***	0.004	-0.016***	0.047**	0.015***	-0.005	-0.017***
	(2.99)	(6.62)	(1.19)	(-3.63)	(2.50)	(5.04)	(-1.44)	(-3.71)
4-5	0.004	0.035***	-0.001	-0.039***	0.072***	0.021***	-0.012**	-0.046***
	(1.23)	(7.47)	(-0.28)	(-5.26)	(2.92)	(4.78)	(-2.17)	(-5.50)
6-7	0.005	0.055***	-0.018**	-0.044***	0.096***	0.024***	-0.024***	-0.052***
	(1.25)	(8.93)	(-2.40)	(-4.88)	(3.70)	(4.46)	(-3.04)	(-4.99)
8-10	-0.011**	0.057***	-0.043***	-0.074***	0.102***	0.008	-0.058***	-0.058***
	(-2.03)	(7.77)	(-4.78)	(-6.55)	(3.84)	(1.15)	(-5.47)	(-3.24)
11-15	-0.029***	0.080***	-0.063***	-0.115***	0.127***	-0.031***	-0.105***	
	(-4.16)	(9.19)	(-6.15)	(-8.39)	(4.64)	(-3.42)	(-7.15)	
≥ 16	-0.086***	0.100***	-0.101***	-0.171***	0.111***	-0.134***	-0.141***	
	(-9.07)	(8.75)	(-7.97)	(-10.66)	(3.88)	(-9.99)	(-6.01)	
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	136,349	55,273	44,587	35,043	62,483	52,168	14,821	6,877
Adj R^2	0.820	0.928	0.899	0.917	0.775	0.843	0.896	0.936

Table III
Passive 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 passive institutional ownership. The table tabulates the coefficient estimates (β_{1991}-β_{2020}) from their respective versions of the following OLS regression of the classified board indicator (*CB*) on controls (regressions are estimated separately for each firm age group):

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

where $Year_t$ equals one for observations in year group t, and zero otherwise, *IndexIO* equals the fraction of a firm's shares owned by index funds (the Big Three or quasi-indexers), *NonIndexIO* equals the fraction of a firm's shares owned by non-index institutional investors, *CS* denotes one of the two *IndexIO* 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 the Appendix), which include $Ln(MVE_{t-1})$, $Delaware_t$, and $S\&P\ 1500_t$, and 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 = Big Three IO				CS = Quasi IO			
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	-0.002	0.008	0.000	0.092***	0.001	-0.001	0.005	0.088***
	(-0.37)	(0.38)	(0.05)	(4.29)	(0.13)	(-0.09)	(1.02)	(9.15)
96-00 × CS	-0.003	0.006	0.017	0.110***	-0.001	0.006*	0.006	0.068***
	(-0.68)	(0.30)	(1.58)	(5.44)	(-0.16)	(1.81)	(1.07)	(8.89)
01-05 × CS	0.000	0.009	0.033**	0.098***	-0.002	0.004	0.011**	0.045***
	(0.02)	(0.76)	(2.16)	(5.92)	(-0.47)	(1.09)	(1.98)	(7.13)
06-10 × CS	-0.014	-0.010	0.003	-0.028***	-0.002	0.003	0.000	0.007
	(-1.58)	(-1.56)	(0.29)	(-3.91)	(-0.57)	(0.80)	(0.07)	(1.40)
11-15 × CS	0.003	-0.017**	-0.002	-0.064***	0.002	-0.003	-0.007	-0.022***
	(0.66)	(-2.30)	(-0.23)	(-7.65)	(0.51)	(-0.62)	(-0.95)	(-3.44)
16-20 × CS	0.008*	-0.008	-0.001	-0.048***	-0.003	-0.003	-0.015	-0.052***
	(1.80)	(-1.56)	(-0.14)	(-6.61)	(-0.63)	(-0.68)	(-1.52)	(-6.74)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	19,145	24,829	19,294	69,508	19,145	24,829	19,294	69,508
Adj R^2	0.967	0.960	0.960	0.821	0.967	0.960	0.960	0.819

Table IV
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 table tabulates the coefficient estimates (β_{1991}-β_{2020}) from their respective versions of the following OLS regression of the classified board indicator (*CB*) on controls (regressions are estimated separately for each firm age group):

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

where $Year_t$ 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 market value of equity (*Firm Size* is normalized to have a standard deviation of one to ease comparisons), *CS* denotes one of these two cross-sectional variables, X_{it} are firm-level characteristics (defined in the Appendix), which include $Ln(MVE_{t-1})$ (not in columns (5) to (8)), $Delaware_t$, IO_t, and $S\&P\ 1500_t$ (not in columns (1) to (4)), and 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(MVE)			
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	0.005	-0.017	0.001	0.132***	0.008	0.011	0.014**	0.098***
	(0.22)	(-1.51)	(0.10)	(10.18)	(1.04)	(1.36)	(2.17)	(9.34)
96-00 × CS	-0.015	0.008	0.015	0.107***	0.010*	0.013***	0.018***	0.082***
	(-1.35)	(0.84)	(1.64)	(9.34)	(1.93)	(2.94)	(2.58)	(8.93)
01-05 × CS	-0.010**	0.009	0.018	0.089***	-0.000	0.011***	0.010	0.061***
	(-2.40)	(1.07)	(1.44)	(7.69)	(-0.02)	(2.77)	(1.52)	(7.54)
06-10 × CS	-0.012	0.007	0.002	-0.011	-0.011	0.001	-0.014*	0.004
	(-1.17)	(0.58)	(0.14)	(-0.90)	(-1.54)	(0.12)	(-1.86)	(0.44)
11-15 × CS	-0.012	-0.017	-0.011	-0.117***	-0.011	-0.011	-0.019**	-0.051***
	(-0.99)	(-1.60)	(-0.63)	(-8.28)	(-1.40)	(-1.36)	(-2.09)	(-5.61)
16-20 × CS	0.003	-0.027**	-0.010	-0.159***	-0.012*	-0.016**	-0.021**	-0.067***
	(0.59)	(-2.11)	(-0.50)	(-10.32)	(-1.88)	(-2.06)	(-2.35)	(-6.93)
Controls	✓	✓	✓	✓	✓	✓	✓	`✓
Observations	19,145	24,829	19,294	69,508	19,145	24,829	19,294	69,508
Adj R^2	0.967	0.960	0.960	0.821	0.967	0.960	0.960	0.824

Table V
Classified Boards and Tobin's Q

This table reports results from OLS regressions relating firm value to classified boards over the period 1991 to 2020 (Panel A), 1991 to 2000 (Panel B), 2001 to 2010 (Panel C), and 2011 to 2020 (Panel D). The dependent variable *Tobin's Q* is the market value of assets scaled by the book value of assets, and *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 included in all regressions (and defined in the Appendix) are *Ln*(*Assets*$_{t-1}$), *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	Age 1	Age 2	Age 3-4	Age 5-6	Age 7-9	Age ≥ 10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CB	0.161***	-0.041	-0.099**	-0.153***	-0.129***	-0.110***	-0.094***
	(2.76)	(-0.87)	(-2.23)	(-3.87)	(-3.31)	(-2.88)	(-3.61)
Year & SIC2 FEs	✓	✓	✓	✓	✓	✓	✓
Observations	6,215	7,376	7,381	13,697	12,126	15,429	74,480
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	0.153**	-0.071	-0.099*	-0.177***	-0.160***	-0.176***	-0.142***
	(2.09)	(-1.16)	(-1.66)	(-3.21)	(-2.71)	(-2.84)	(-4.26)
Year & SIC2 FEs	✓	✓	✓	✓	✓	✓	✓
Observations	4,046	4,374	4,077	6,954	5,539	6,460	24,367
Adj R^2	0.328	0.231	0.237	0.255	0.236	0.228	0.152

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	-0.058	-0.145**	-0.075	-0.129***
	(1.84)	(0.34)	(-1.16)	(-0.89)	(-2.34)	(-1.42)	(-4.03)
Year & SIC2 FEs	✓	✓	✓	✓	✓	✓	✓
Observations	1,044	1,534	1,941	4,249	4,231	6,171	26,200
Adj R^2	0.232	0.194	0.248	0.301	0.261	0.252	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	-0.210**	-0.013	-0.044	-0.023
	(1.53)	(-0.21)	(-0.97)	(-2.02)	(-0.14)	(-0.45)	(-0.51)
Year & SIC2 FEs	✓	✓	✓	✓	✓	✓	✓
Observations	1,102	1,454	1,349	2,487	2,353	2,795	23,911
Adj R^2	0.224	0.245	0.275	0.238	0.243	0.236	0.202

INTERNET APPENDIX FOR

"THIRTY YEARS OF CHANGE: THE EVOLUTION OF CLASSIFIED BOARDS"

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

This Internet Appendix supplements the main article. Section I provides additional details on how we predict whether a firm has a classified board using the RF Classifier. Section II presents an example of the "Proposal No. 1" paragraph from an annual proxy statement. Section III contains additional figure and tables of supplementary analyses and robustness checks.

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I. Predicting Classified Board Status using the RF Classifier

A. 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 and manually inspecting the data and merging the data to the CRSP-Compustat database, our final sample that uses machine learning has 110,176 unique firm-year observations. Table IA.I summarizes how each cleaning and merging step affected our sample.

Table IA.I
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. Internet Appendix Section II 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 10 words before and after each instance the keyword is found. We require the word "director" or "board" to appear within these 10 words for us to consider it a valid keyword match. This restriction is intended to remove instances in which "class" refers to share classes. Next, we search the DEF 14A filings for variations of the word "term" and then keep the 10 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 10 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.[23]

Our third step is to clean the data and obtain firm identifiers that we 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.
4. There are also situations in which 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

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

of this problem is that firms incorrectly file a document, such as a DEFM 14A, as a DEF 14A. These errors are usually observable because the DEFM 14A (or other document) filing date 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. We keep the earliest filed DEF 14A for these cases, as most DEF 14A filings are filed seven to nine 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 67: "Holding & Other Investment Offices." These holdings companies often discuss companies they hold in their DEF 14A filings, and it is 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.

B. 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. We use 80% of these observations as a training sample and the remaining 20% as an out-of-sample test data set.

Our final step is determining the RF Classifier model parameters and making 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 data set 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., fewer errors). On the other hand, setting the number of trees and levels in each tree too high 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 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 that 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.[24] The optimal number of predictors we use for each tree is the logarithm of the total number of predictors to the base 2. We then use the "best RF" to predict the classified board status for the out-of-sample test data set and evaluate the algorithm's success. We then extend the predictions to the universe of firms with DEF 14A filings.

C. Validating our Classified Board Predictions and Manually Inspecting the Data Set

Given that our application of the RF Classifier is a new approach to predicting classified board status, validating our measure and assessing the out-of-sample prediction accuracy is important. 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 99.3% (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 99.9%, with all but five of the inaccurate predictions coming from false negatives. Our out-of-sample accuracy rate is also high at 97.3% (1.5% false negatives and 1.2% 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 22.2% (21.3% false positives and 0.98% false negatives). Manual investigation indicates that the keyword 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

[24] The average level of depth in our testing sample is 84, and the minimum (maximum) level of depth is 54 (129).

decreases to 8.7% (6.7% false positives and 2.0% false negatives). Modifying the keyword search this way highlights the shortcomings of keyword searches – narrowing the search 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 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 Section I.A with the keywords “class” (without any refinements) and “term,” the RF Classifier produces an error rate for the training sample of 1.2% (0.08% false positives and 1.2% false negatives) and an out-of-sample error rate of 3.3% (1.4% false positives and 1.9% false negatives). In other words, the RF Classifier for the combined training and out-of-sample data sets reduces the error rate of the refined keyword search algorithm by 81.0%.

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. Concerning discrepancies between our predictions and the ISS database, they 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 related to a merger, not the annual proxy statement. This situation rarely occurs. 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) 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 the 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, 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.

II. 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[25]

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.

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

III. Additional Results

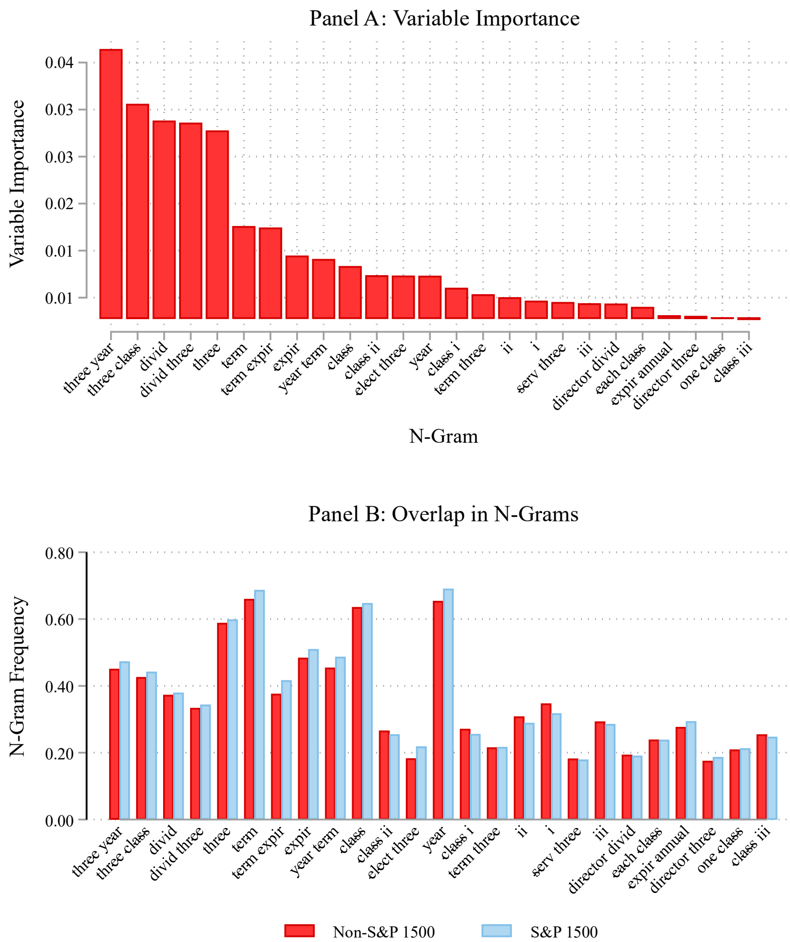


Figure IA.1. Variable importance and N-gram overlap. Panel A tabulates the variable importance values of the top 25 N-Grams that predict a firm's classified board status. Panel B tabulates the fraction of S&P 1500 and non-S&P 1500 firms mentioning these N-Grams.

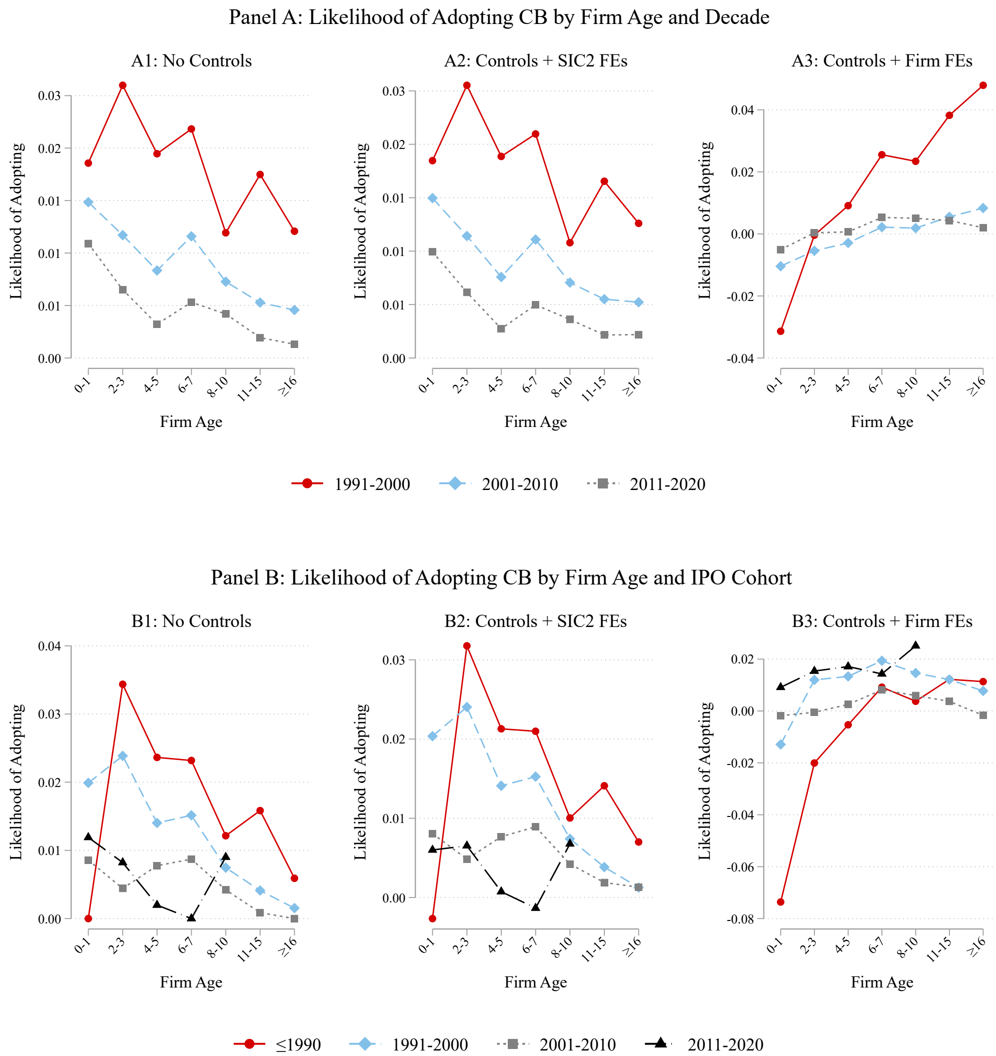


Figure IA.2. Likelihood of adopting classified boards by firm age, decade, and IPO cohort. Panel A (B) shows the likelihood of a firm adopting a classified board over time by firm age group and decade (IPO cohort). The panels plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective 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 (regressions are estimated separately for each decade in Panel A and for each IPO cohort in Panel B):

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

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

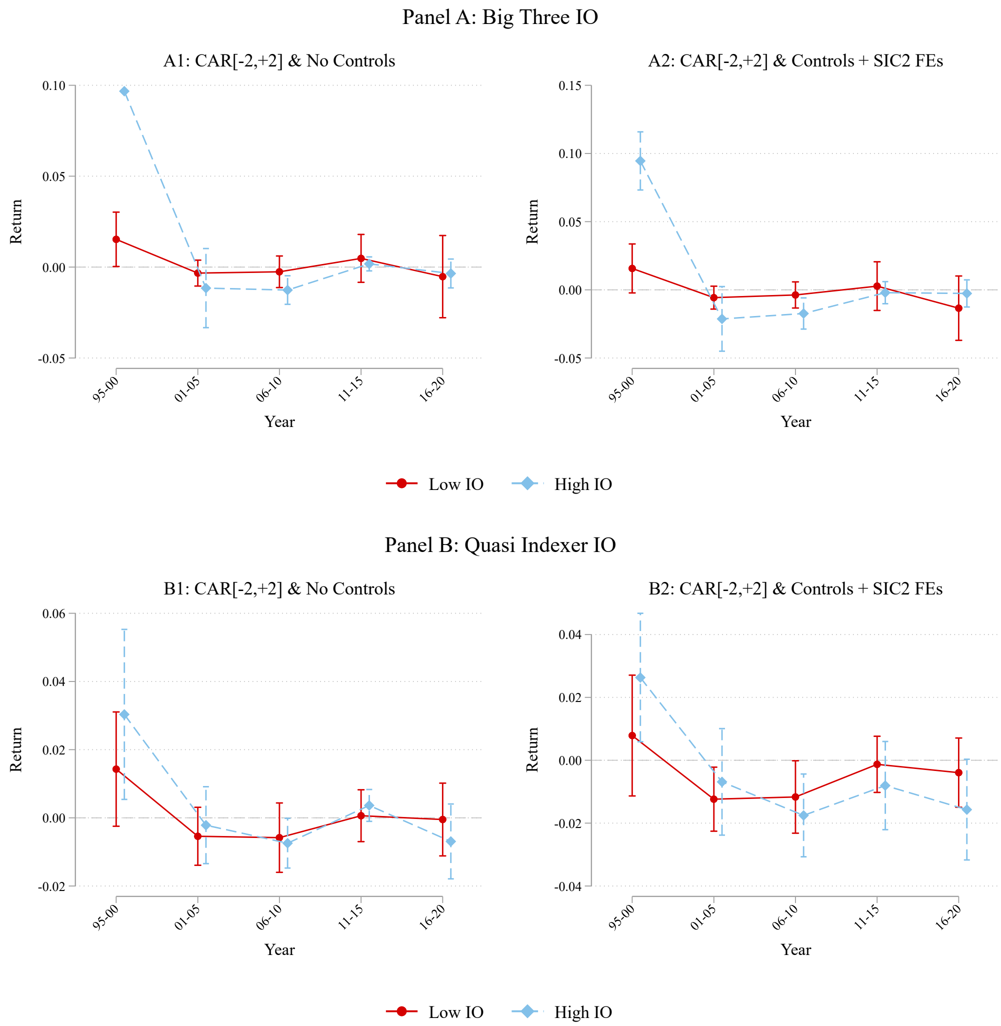


Figure IA.3. Announcement CARs to board declassification over time: Effect of passive institutional ownership. The figure tabulates the ±2-day CAR around annual shareholder meetings that vote to declassify a firm's board, respectively, over the period 1995 to 2020, where samples are split into above and below median values of *Big 3 IO* (Panel A) and *Quasi IO* (Panel B). Parameters used to calculate CARs are estimated using the market model and the CRSP equal-weighted index over the [-210,-11] trading days before the meeting date. The panels plot the coefficient estimates (β_{1995}-β_{2020}) from their respective versions of the OLS regression

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

where $Year_t$ equals one for observations in year group t, and zero otherwise, X_{it} are firm-level characteristics measured before the announcement date (defined in the Appendix), which include $Ln(MVE_{t-1})$, IO_{t-1}, $Delaware_{t-1}$, and $S\&P\ 1500_{t-1}$, and η_k are two-digit SIC industry fixed effects. 90% confidence intervals based on standard errors clustered by firm are reported.

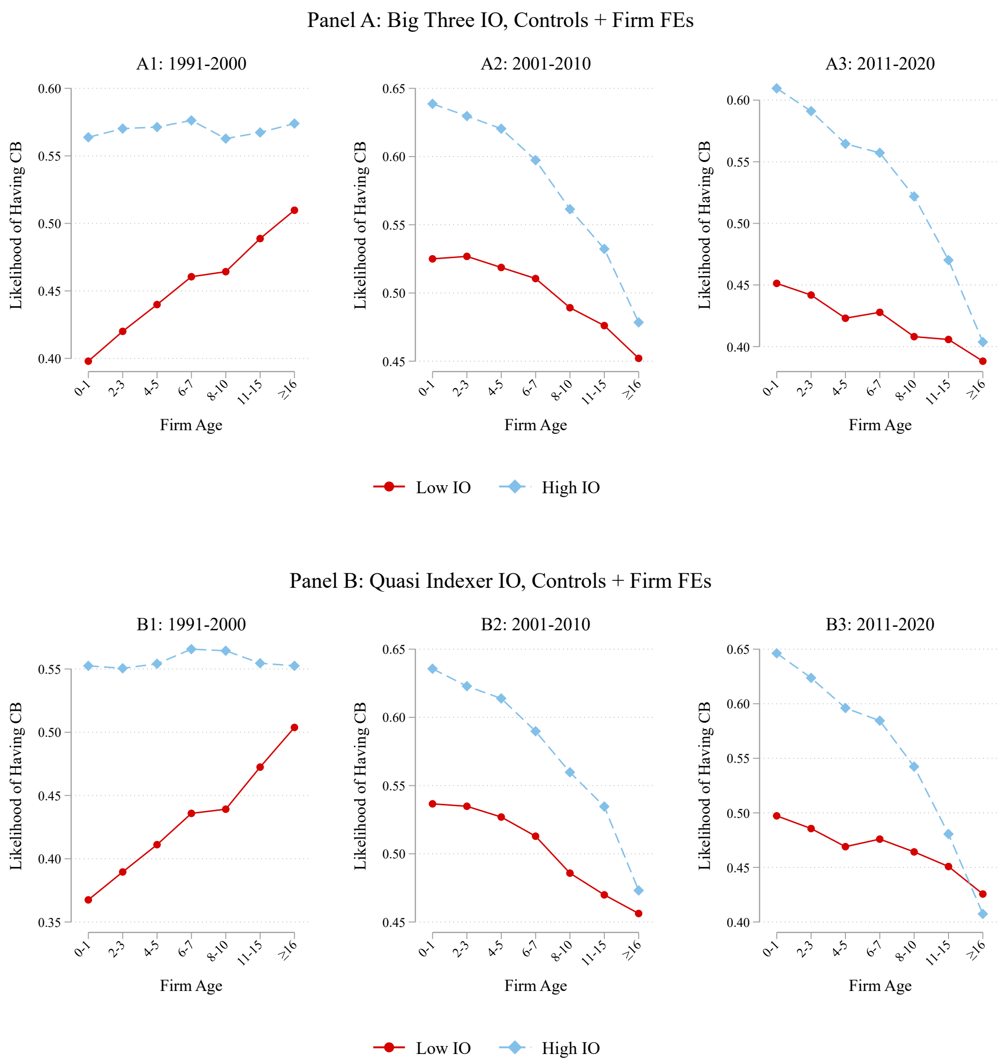


Figure IA.4. Use of classified boards by firm age and decade: Effect of passive institutional ownership. The figure shows the fraction of firms with a classified board by firm age group and decade. The panels plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of the classified board indicator (*CB*) on controls, where samples are split into above and below median values of *Big 3 IO* (Panel A) and *Quasi IO* (Panel B) (regressions are estimated separately for each decade):

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

where *Big 3 IO* is the fraction of a firm's shares owned by the Big Three institutional investors (Blackrock, State Street, and Vanguard), *Quasi IO* is the fraction of a firm's shares owned by institutional investors classified as quasi-indexers in Bushee and Noe (2000) and Bushee (2001), Age_{it} equals one if firm age is in age group *a,* and zero otherwise, X_{it} are firm-level characteristics (defined in the Appendix), which include $Ln(MVE_{t\text{-}1})$, IO_t, $Delaware_t$, and $S\&P\ 1500_t$, and η_k and γ_i are two-digit SIC industry and firm fixed effects, respectively.

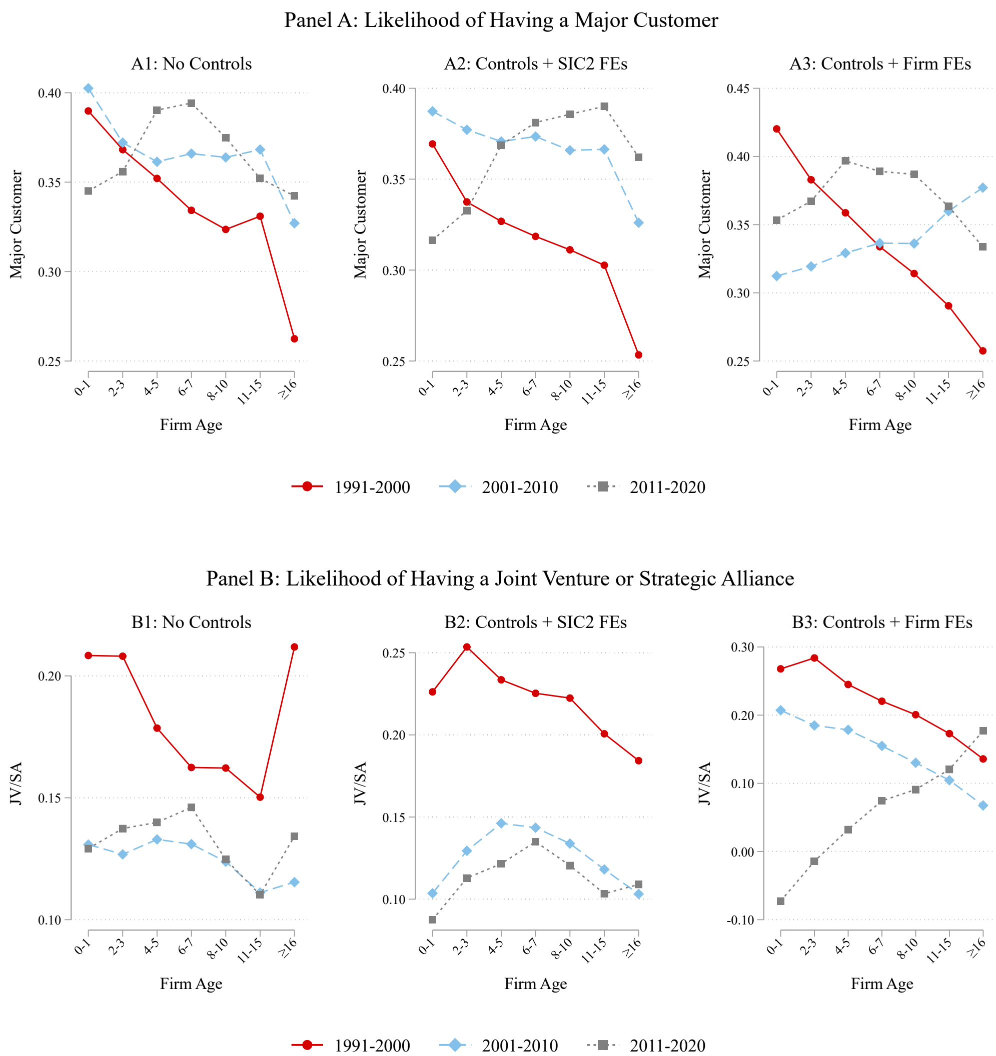
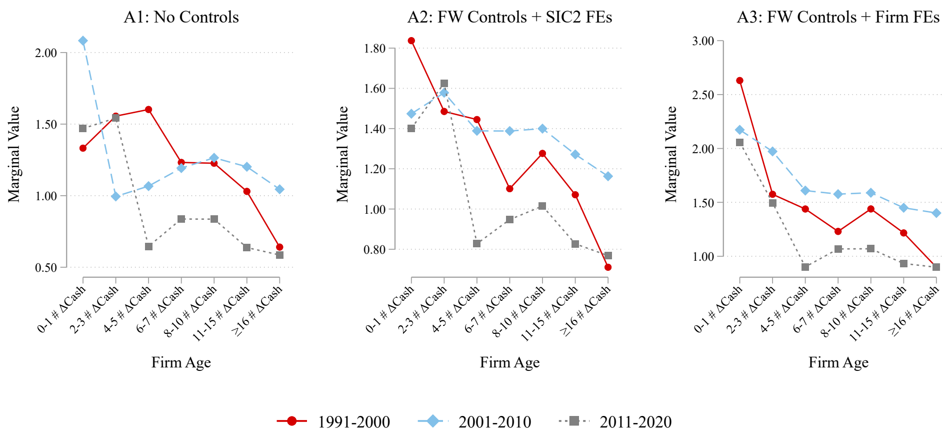


Figure IA.5. Importance of stakeholders by firm age and decade. This figure shows the likelihood of having a major customer that accounts for at least 10% of a firm's revenues (*Major Customer*) in Panel A and having a joint venture or strategic alliance (*JV/SA*) in Panel B by firm age group and decade. The panels plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of *Major Customer* and *JV/SA* on controls (regressions are estimated separately for each decade):

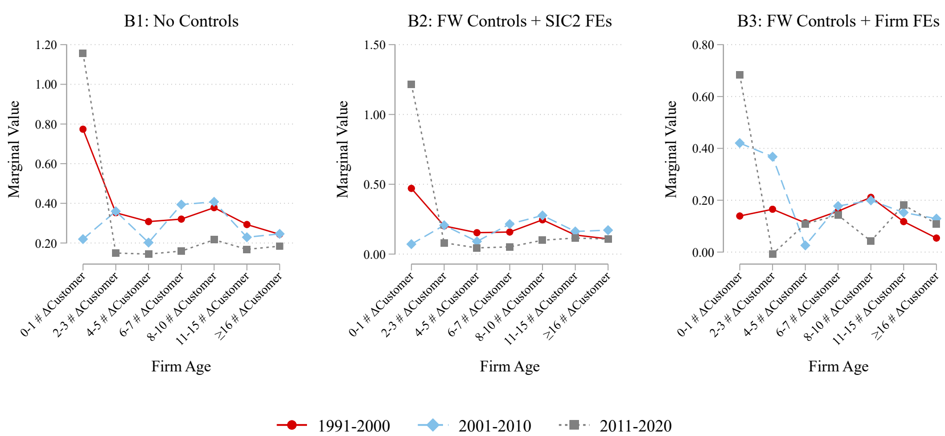
$$Major\ Customer_{it}\ or\ JV/SA_{it} = \sum_{a=0}^{\geq 16} \omega_a Age_{it} + \Gamma X_{it} + \eta_k + \gamma_i + \varepsilon_{it},$$

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

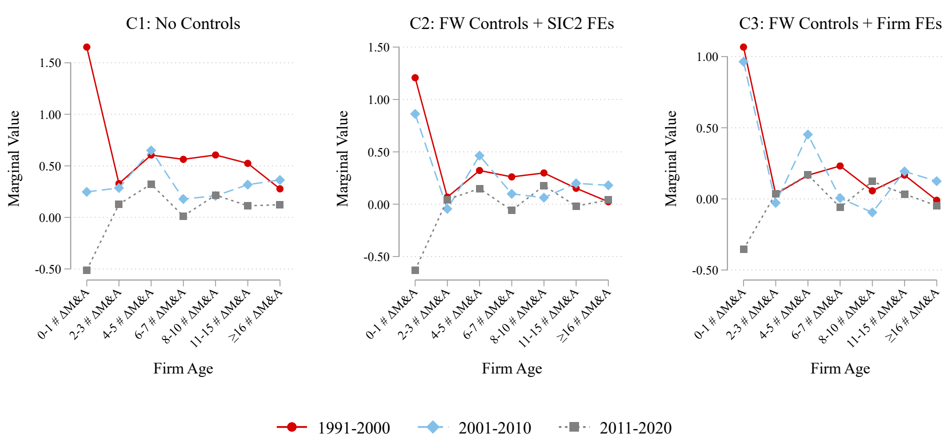
Panel A: Marginal Value of Cash Holdings



Panel B: Marginal Value of Sales to Large Customer



Panel C: Marginal Value of Diversifying Acquisitions



Panel D: Marginal Value of Durable Product Sales

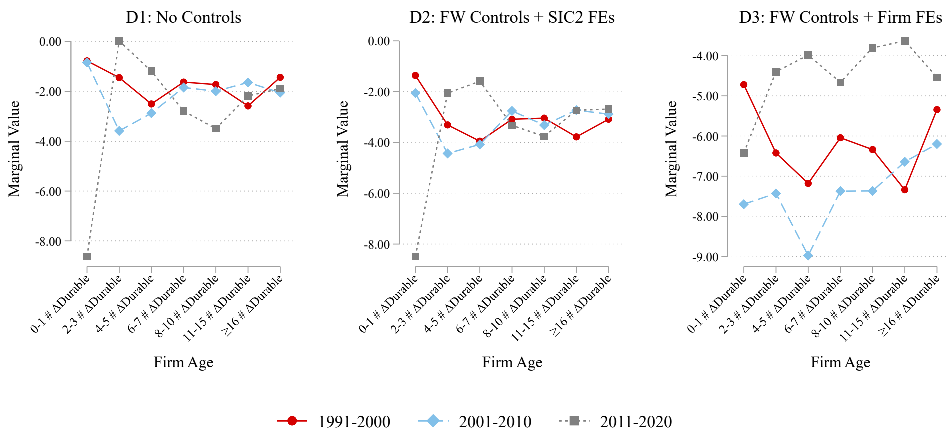


Figure IA.6. Value of costs and benefits of classified boards by firm age and decade. This figure shows the value of cash (Panel A), sales to major customers (Panel B), diversifying acquisitions (Panel C), and durable product sales (Panel D) by firm age group and decade. We estimate the marginal value of each cost and benefit based on a modified Faulkender and Wang (2006) marginal value of cash regression following Johnson, Karpoff, and Yi (2022). The sample period is from 1991 to 2020. The panels plot the coefficient estimates (ω_0-$\omega_{\geq 16}$, β_0- $\beta_{\geq 16}$, δ_0- $\delta_{\geq 16}$, and θ_0- $\theta_{\geq 16}$,) from their respective versions of the following OLS regressions (regressions are estimated separately for each decade):

$$r_{it} - R_{it}^{B} = \sum_{a=0}^{\geq 16}\left(\omega_a Age_{it} \times \frac{\Delta Cash_{it}}{M_{it-1}} + \beta_a Age_{it} \times \frac{\Delta Customer_{it}}{M_{it-1}} + \delta_a Age_{it} \times \frac{\Delta M\&A_{it}}{M_{it-1}} + \theta_a Age_{it} \times \frac{\Delta Durable_{it}}{M_{it-1}}\right), + \Gamma X_{it} + \eta_k + \gamma_i + \varepsilon_{it},$$

where the dependent variable is a firm's stock return over its fiscal year less the return on a size and book-to-market matched portfolio, Age_{it} equals one if firm age is in age group a, and zero otherwise, $\Delta Cash$, $\Delta Customer$, $\Delta M\&A$ and $\Delta Durable$ are changes in cash holdings, sales to a firm's largest customer, deal value of diversifying acquisitions, and durable product sales, X_{it} are control variables from Faulkender and Wang (FW, 2006) and include changes in earnings, net assets, R&D expenditures, interest, and dividends (all scaled by lagged market value of equity). These controls also include net financing and lagged cash holdings scaled by lagged market value of equity and the market leverage ratio. η_k and γ_i are two-digit SIC industry and firm fixed effects, respectively.

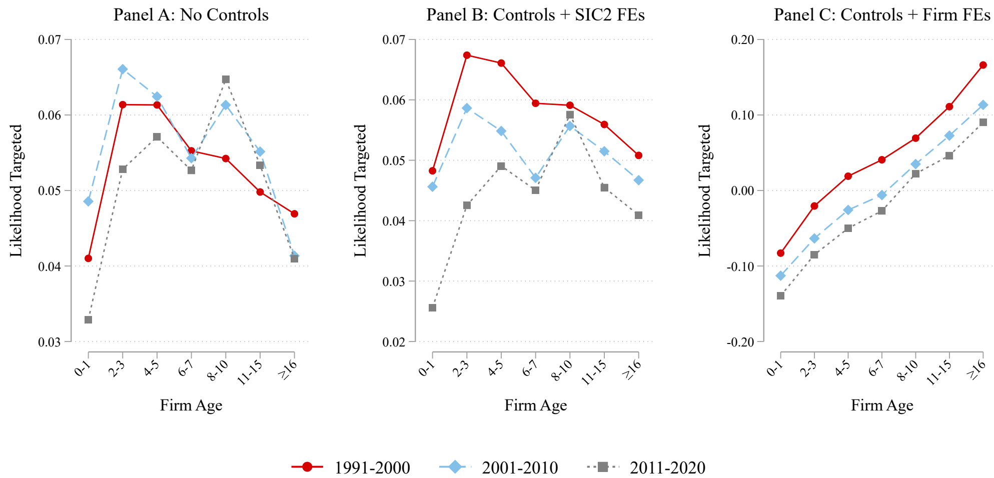


Figure IA.7. Likelihood of being an M&A target by firm age and decade. The figure shows the likelihood that a firm is targeted for a takeover over time by firm age group and decade. M&A data are from SDC. Firms are considered targeted if they receive a bid from a potential acquirer that owns less than 50% of the firm before the bid and seeks to own more than 50% of the firm after the deal is completed. The panels 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 (regressions are estimated separately for each decade):

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

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

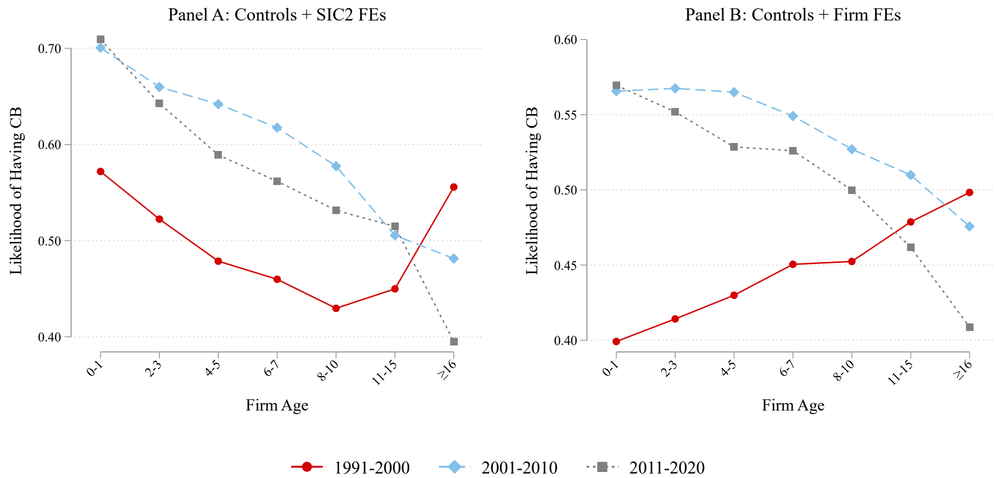


Figure IA.8. Use of classified boards by firm age and decade: Additional controls. The figure shows the fraction of firms with a classified board by firm age group and decade. The panels plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of the classified board indicator (*CB*) on controls (regressions are estimated separately for each decade):

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

where Age_{it} equals one if firm age is in age group *a,* and zero otherwise, X_{it} are firm-level characteristics which include $Ln(MVE_{t\text{-}1})$, $Ln(MVE_{t\text{-}1})^2$, $Ln(MVE_{t\text{-}1})^3$, IO_t, $Delaware_t$, *S&P 1500*$_t$, *Tobin's* Q_t, $OpROA_t$, $BookLev_t$, $Capex_t$, $Ln(Turnover_t)$, $RetVol_t$, and $Ln(\#Analysts_t)$, and η_k and γ_i are two-digit SIC industry and firm fixed effects, respectively. *OpROA* is operating income before depreciation and amortization scaled by book assets (*oibdp/at*). *BookLev* is book value of debt scaled by book assets [(*dltt*+*dlc*)/*at*]. *Capex* is capital expenditures scaled by book assets (*capx/at*). *Turnover* is monthly trading volume scaled by shares outstanding and averaged over a firm's fiscal year. *RetVol* is the standard deviation of monthly returns over a firm's fiscal year. *#Analysts* is the average number of analysts covering a firm over its fiscal year. Other variables are defined in the Appendix.

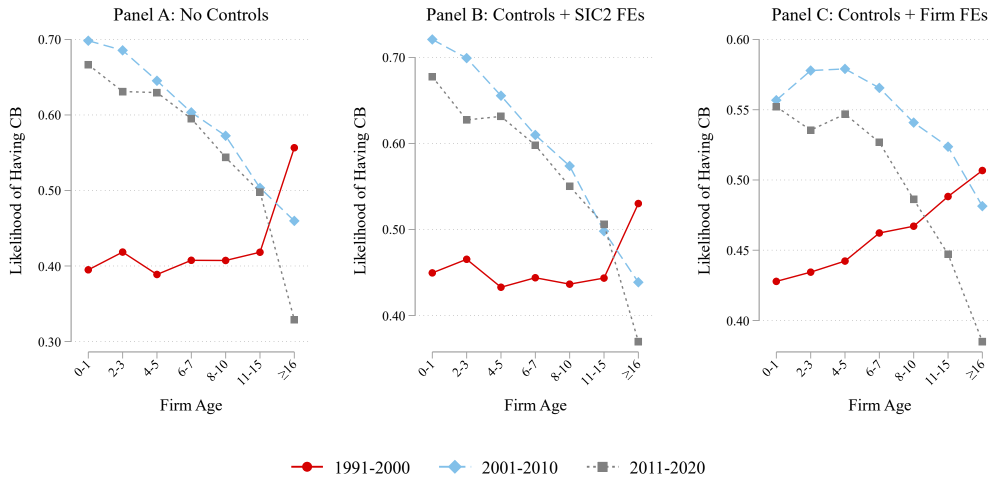


Figure IA.9. Survivorship sample: Use of classified boards by firm age and decade. The figure shows the fraction of firms with a classified board by firm age group and decade. We restrict the sample to firms that appear in the sample for all 10 years during a decade. The panels plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of the classified board indicator (*CB*) on controls (regressions are estimated separately for each decade):

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

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

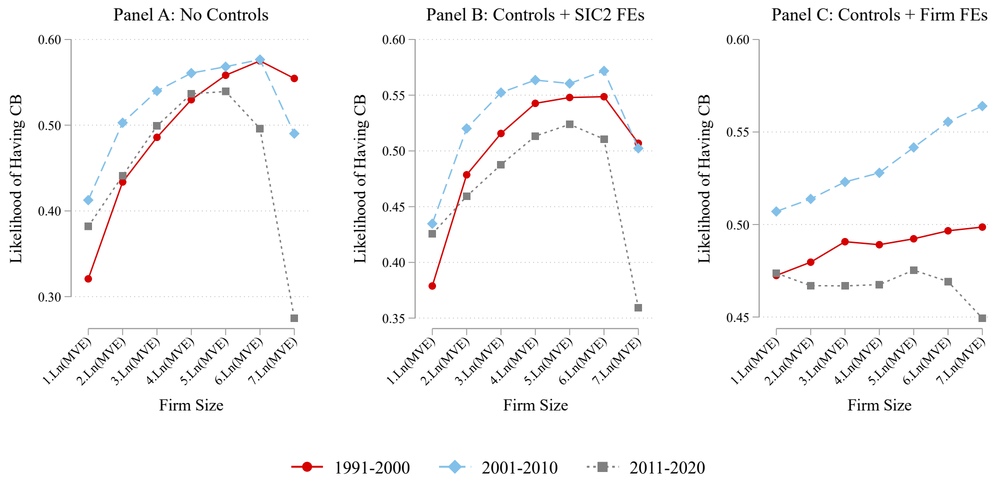


Figure IA.10. Use of classified boards by firm size and decade. The figure shows the fraction of firms with a classified board by firm size group and decade. The panels plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression of the classified board indicator (*CB*) on controls (regressions are estimated separately for each decade):

$$CB_{it} = \sum\nolimits_{a=0}^{7} \omega_a Size_{it} + \Gamma X_{it} + \eta_k + \gamma_i + \varepsilon_{it},$$

where $Size_{it}$ equals one if firm market capitalization is in size group group *a,* and zero otherwise, X_{it} are firm-level characteristics (defined in the Appendix), which include *Ln*(Age_t), IO_t, $Delaware_t$, and *S&P* 1500_t, and η_k and γ_i are two-digit SIC industry and firm fixed effects, respectively.

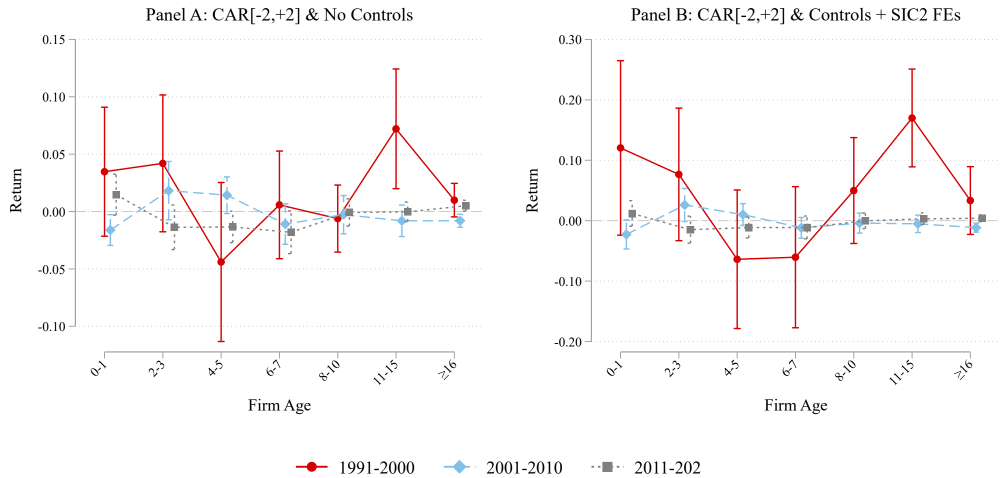


Figure IA.11. Announcement CARs to board declassification by firm age and decade. Panels A and B tabulate ±2-day CARs around annual shareholder meetings that vote to declassify a firm's board over the period 1995 to 2020. Parameters used to calculate CARs are estimated using the market model and the CRSP equal-weighted index over the [-210,-11] trading days before the meeting date. The panels plot the coefficient estimates (ω_0-$\omega_{\geq 16}$) from their respective versions of the following OLS regression:

$$CAR[-2,+2] = \sum_{a=0}^{\geq 16} \omega_a Age_{it} + \Gamma X_{it-1} + \eta_k + \varepsilon_{it},$$

where Age_{it} equals one if firm age is in age group *a,* and zero otherwise, X_{it} are firm-level characteristics measured before the announcement date (defined in the Appendix), which include $Ln(MVE_{t-1})$, IO_{t-1}, $Delaware_{t-1}$, and $S\&P\ 1500_{t-1}$, and η_k are two-digit SIC industry fixed effects. 90% confidence intervals based on standard errors clustered by firm are reported.

Table IA.II
R&D Expenditures, Intangible Assets, Collective Action Costs, 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 R&D expenditures, intangible assets, and bid-ask spreads. The table tabulates the coefficient estimates (β_{1991}-β_{2020}) from their respective versions of the following OLS regression of the classified board indicator (*CB*) on controls (regressions are estimated separately for each firm age group):

$$CB_{it} = \sum_{t=1991}^{2020} [\beta_t(CS_{it} \times Year_t)] + \Gamma X_{it} + \gamma_i + \tau_t + \varepsilon_{it},$$

where $Year_t$ equals one for observations in year group *t,* and zero otherwise, *CS* equals R&D expenditures scaled by sales (*xrd/sale*), intangible assets (1-*ppent/at*), or *Ln(Bid-Ask Spread)*, respectively (all *CS* variables are normalized to have a standard deviation of one to ease comparisons), X_{it} are firm-level characteristics (defined in the Appendix), which include $Ln(MVE_{t-1})$, IO_{t-1}, $Delaware_t$, and $S\&P\ 1500_t$, and 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 = R&D Expenditures				CS = Intangible Assets				CS = Ln(Bid-Ask Spread)			
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	-0.005	-0.004	0.001	-0.016*	-0.007	0.000	-0.006	-0.018*	0.000	0.003	-0.015*	-0.072***
	(-1.29)	(-1.09)	(0.39)	(-1.91)	(-1.49)	(0.05)	(-1.08)	(-1.72)	(0.01)	(0.22)	(-1.65)	(-5.47)
96-00 × CS	-0.004	0.000	0.001	-0.017***	-0.006	-0.007	-0.006	-0.012	-0.015**	-0.004	-0.022***	-0.036***
	(-1.19)	(0.01)	(0.74)	(-5.39)	(-1.38)	(-1.30)	(-1.07)	(-1.33)	(-2.45)	(-0.72)	(-2.65)	(-3.32)
01-05 × CS	-0.000	-0.001	-0.003*	-0.018***	-0.010	-0.006	-0.000	-0.012	-0.003	-0.002	-0.024***	0.002
	(-0.18)	(-0.62)	(-1.75)	(-3.32)	(-1.33)	(-1.19)	(-0.07)	(-1.40)	(-0.46)	(-0.31)	(-3.34)	(0.21)
06-10 × CS	0.000	0.001	0.001	-0.005	-0.011	-0.007	-0.004	0.001	0.005	0.003	0.001	0.060***
	(0.47)	(0.33)	(0.51)	(-1.07)	(-1.58)	(-1.32)	(-0.54)	(0.11)	(0.74)	(0.45)	(0.08)	(7.12)
11-15 × CS	-0.000	-0.001	-0.001	0.009***	-0.015*	-0.008	-0.002	0.007	0.004	0.011	0.002	0.106***
	(-0.11)	(-1.22)	(-1.17)	(3.77)	(-1.92)	(-1.54)	(-0.28)	(0.68)	(0.67)	(1.49)	(0.29)	(12.29)
16-20 × CS	0.001	-0.001**	0.002	0.016***	-0.015**	-0.001	0.004	0.005	0.005	0.013*	0.006	0.128***
	(1.26)	(-2.05)	(1.55)	(4.63)	(-2.32)	(-0.13)	(0.40)	(0.46)	(0.74)	(1.84)	(0.89)	(13.32)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	18,095	23,752	18,661	68,965	18,811	24,170	18,795	68,791	18,931	24,331	18,835	68,525
Adj R^2	0.968	0.961	0.961	0.814	0.968	0.961	0.960	0.815	0.967	0.961	0.960	0.822

Table IA.III
Firm Age × Size Frequencies

This table tabulates the frequencies of firm age and firm size. We categorize firms independently by market capitalization and firm age into five groups, each forming a 5×5 matrix of age and size quintiles.

		Size Quintiles					
		1	2	3	4	5	Total
Age Quintiles	1	5,833 4.26%	6,871 5.01%	6,966 5.08%	5,588 4.08%	2,422 1.77%	27,680 20.20%
	2	7,900 5.77%	7,225 5.27%	6,371 4.65%	5,295 3.86%	3,040 2.22%	29,831 21.77%
	3	5,940 4.33%	5,644 4.12%	5,182 3.78%	4,600 3.36%	3,496 2.55%	24,862 18.14%
	4	5,464 3.99%	5,091 3.72%	5,569 4.06%	5,974 4.36%	6,092 4.45%	28,190 20.57%
	5	2,270 1.66%	2,575 1.88%	3,319 2.42%	5,949 4.34%	12,356 9.02%	26,469 19.32%
	Total	27,407 20.00%	27,406 20.00%	27,407 20.00%	27,406 20.00%	27,406 20.00%	137,032 100.00%

Table IA.IV
Classified Boards and Tobin's Q: Delaware×Year FEs

This table reports results from OLS regressions relating firm value to classified boards over the period 1991 to 2020 (Panel A), 1991 to 2000 (Panel B), 2001 to 2010 (Panel C), and 2011 to 2020 (Panel D). The dependent variable *Tobin's Q* is the market value of assets scaled by the book value of assets, and *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 included in all regressions (and defined in the Appendix) are $Ln(Assets_{t-1})$, IO_t, $Delaware_t$ *(DE)*, 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	Age 1	Age 2	Age 3-4	Age 5-6	Age 7-9	Age ≥ 10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CB	0.171***	-0.038	-0.100**	-0.155***	-0.132***	-0.111***	-0.094***
	(2.94)	(-0.81)	(-2.26)	(-3.92)	(-3.40)	(-2.93)	(-3.63)
DE×Year & SIC2 FEs	✓	✓	✓	✓	✓	✓	✓
Observations	6,215	7,376	7,381	13,697	12,126	15,429	74,480
Adj R^2	0.301	0.234	0.249	0.254	0.238	0.229	0.180
Panel B: Sample period 1991-2000							
	Age 0	Age 1	Age 2	Age 3-4	Age 5-6	Age 7-9	Age ≥ 10
CB	0.157**	-0.071	-0.102*	-0.179***	-0.159***	-0.179***	-0.141***
	(2.15)	(-1.15)	(-1.72)	(-3.23)	(-2.69)	(-2.91)	(-4.24)
DE×Year & SIC2 FEs	✓	✓	✓	✓	✓	✓	✓
Observations	4,046	4,374	4,077	6,954	5,539	6,460	24367
Adj R^2	0.335	0.233	0.237	0.256	0.237	0.228	0.152
Panel C: Sample period 2001-2010							
	Age 0	Age 1	Age 2	Age 3-4	Age 5-6	Age 7-9	Age ≥ 10
CB	0.242*	0.042	-0.099	-0.061	-0.142**	-0.074	-0.129***
	(1.88)	(0.42)	(-1.25)	(-0.93)	(-2.28)	(-1.41)	(-4.02)
DE×Year & SIC2 FEs	✓	✓	✓	✓	✓	✓	✓
Observations	1,044	1,534	1,941	4,249	4,231	6,171	26,200
Adj R^2	0.235	0.190	0.246	0.302	0.263	0.253	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	0.253	-0.041	-0.123	-0.219**	-0.028	-0.042	-0.024
	(1.60)	(-0.32)	(-0.98)	(-2.09)	(-0.31)	(-0.43)	(-0.54)
DE×Year & SIC2 FEs	✓	✓	✓	✓	✓	✓	✓
Observations	1,102	1,454	1,349	2,487	2,353	2,795	23,911
Adj R^2	0.221	0.247	0.274	0.238	0.245	0.236	0.202

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ECGI is an international non-profit membership organisation that provides a platform for debate and dialogue among academics, policymakers, and business leaders, with a focus on major corporate governance, ESG, and stewardship issues.

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